ISSN 0956-8549

# Polarized Expectations, Polarized Consumption

By

**Rupal Kamdar**
**Walker Ray**

**DISCUSSION PAPER NO 902**

**February 2024**

# Polarized Expectations, Polarized Consumption*

Rupal Kamdar
Indiana University, Bloomington

Walker Ray
London School of Economics

September 19, 2023

**Abstract**

This paper argues that political affiliation plays a central role in shaping household expectations and consumption behavior. Using survey and consumption data of U.S. households, we document five facts. First, household beliefs are well-described by a single factor "sentiment" model, with nearly identical factor structures regardless of political affiliation. Second, sentiment is highly persistent, with one exception: following changes in the White House, "optimists" become "pessimists" (and vice versa). Third, at any given time there is wide dispersion in sentiment across households, which is increasingly driven by political affiliation. Fourth, households have become more likely to justify their economic beliefs using partisan narratives; but outside of elections, the pass-through to sentiment is stable over time. Fifth, consumption responds differentially along party lines following changes in the White House. Standard theories of expectation formation struggle to simultaneously rationalize these facts.

**Keywords:** expectations, voting, consumption

**JEL Classification:** E7, D72, D83

*Kamdar Email: rkamdar@iu.edu. Ray Email: w.d.ray@lse.ac.uk. We thank William Cassidy, Daniel Cooper, Vicente Cuñat, Yuriy Gorodnichenko, Amy Handlan, Dirk Jenter, Yann Koby, Jean-Paul L'Huillier, Igor Makarov, Cameron Peng, David Romer, Nick Sander, Antoinette Schoar, Jenny Tang, and seminar participants at UC Berkeley, Indiana University, London School of Economics, Brown University, the Federal Reserve Bank of Boston, CEBRA's Annual Meeting, Society of Economic Dynamics, Society of Economic Measurement, and the FRBNY-BOC-ECB Conference on Expectations Surveys for excellent comments. We thank Sergii Drobot for excellent research assistance.

# 1 Introduction

Political polarization in the U.S. is rising.[1] Besides the direct role polarization plays in the political process which generates economic policy, growing divisions across political lines can spill over into how households perceive economic conditions, form expectations about the future, and act on these beliefs. This paper documents five facts which show that political affiliation is an increasingly strong driver of both household expectations and actions.

First, household beliefs about aggregate and personal economic conditions are well-described by a *single factor*. At any given point in time, households fall on a spectrum of optimism to pessimism regarding their economic beliefs; for simplicity, we label this component "sentiment." Both the dimensionality of beliefs and the mapping from sentiment to economic forecasts are nearly identical across all demographic groups. Crucially, this includes political affiliation: conditional on being "optimistic" or "pessimistic," both Democratic and Republican households hold highly similar aggregate and personal economic beliefs.

Second, *within households* we find that sentiment almost always exhibits a high degree of persistence, with one glaring exception: following presidential elections when the White House switches parties, there are large breakdowns of sentiment persistence. At these times, optimistic households become pessimistic (and vice versa). Additionally, the magnitude of this switching behavior has increased over time; the largest changes are observed following the 2016 and 2020 elections. This switching behavior is seen at no other times, including following large macroeconomic shocks, midterm elections, or even following other presidential elections where the White House does not change party.

Third, at any given time *across households* we find wide dispersion in sentiment, a great deal of which is accounted for by political affiliation. Consistent with our results regarding sentiment switching, we find that Democratic households tend to be optimistic at the same time as Republican households are pessimistic (and vice versa). Moreover, the explanatory power of political affiliation has increased over time, and in recent years additional demographic variables explain virtually none of the dispersion in sentiment.

Fourth, there has been a secular rise in *partisan narratives:* when asked to explain their reasoning for their views on either aggregate or personal economic conditions, households are increasingly likely to give government-related explanations. Unsurprisingly, partisan narratives spike following changes in the White House. At these times, changes in partisan narratives are associated with large swings in sentiment. The "pass-through" of changes in partisan narratives to sentiment has increased over time, with the largest effects observed

[1] Among others, Pew Research Center (2014) has documented a long-term increase in negative views of the opposing party or ideology within the U.S.

in the two most recent elections. Outside of changes in the White House, shifts in partisan narratives are associated with modest movements in sentiment; unlike following changes in the White House, this pass-through has been stable over time. This does not imply that households ignore political occurrences outside of presidential elections. To the contrary, we find that partisan narratives are reactive to policy events besides presidential elections.

Fifth, *consumption* responds differentially along party lines following changes in the White House. In the two most recent presidential elections, households affiliated with the winning party immediately increase consumption in the weeks following the outcome of the election relative to those affiliated with the losing party. The differential consumption response is the strongest following the 2016 election. While we find suggestive evidence of similar results following the 2020 election, cleanly identifying the effects of the 2020 election is more difficult because we find markedly different consumption patterns across partisan households following the COVID-19 outbreak.

Taken together, our five facts show that political polarization is an increasingly dominant facet of consumer beliefs and actions. A wide range of consumers' aggregate and personal financial forecasts can be largely attributed to political affiliation, and the predictive power of political affiliation is steadily rising. At the same time, households themselves have become more partisan in their subjective explanations of the determination of economic conditions. In both cases, control of the White House plays an outsized role. Consistent with this finding, consumption also reacts to changes in the White House along party lines.

Our paper is organized as follows. In Section 2, we utilize survey data of U.S. consumers in order to understand how political affiliation affects aggregate and personal economic beliefs. Section 2.2 presents a factor structure analysis of household expectations. We find that beliefs about the current state of the economy, macroeconomic forecasts, and beliefs about personal financial conditions are almost entirely determined by a single component. For ease of exposition we label this factor "sentiment," because consumers from whom we estimate a high value for this first component tend to report optimistic outlooks across a wide range of economic questions. This includes not only forward-looking forecasts but also backward-looking beliefs; and is true for beliefs regarding macroeconomic conditions as well as own personal financial conditions.

Both the dimensionality of beliefs as well as the estimated loadings linking sentiment and expectations are extremely stable across time. Further, our estimated factor structure of beliefs is nearly identical regardless of educational attainment, income or investment levels, or across other demographic variables. Crucially, this similarity extends to political affiliation. In other words, the mapping from sentiment to economic beliefs is essentially the same across Democratic and Republican households.

Next, we analyze the dynamics of economic beliefs. While there is widespread dispersion of sentiment across individuals at any point, in Section 2.3 we find that for any given individual, sentiment is highly persistent. Optimistic households tend to stay optimistic, while pessimistic households tend to stay pessimistic. Rolling regressions show that sentiment autocorrelation is strongly positive in almost all periods. The only exceptions are following presidential elections when the White House changed parties. During these periods, previously optimistic individuals are more likely to become pessimistic; similarly, pessimistic individuals are more likely to become optimistic. This breakdown in sentiment persistence following elections has grown over time, with the most striking switching behavior coming after the 2016 and 2020 presidential elections. While the main analysis focuses on our sentiment factor, we also document strong switching behavior across a range of specific economic beliefs (also further reinforcing the result that our sentiment measure is a useful summary statistic for consumer beliefs). Finally, we analyze high-frequency (daily) dynamics of beliefs around these events and find that sentiment switching occurs immediately following the outcome of elections which result in a change in control of the White House (and remains stable at other times).

Turning to the cross-section of economic beliefs, Section 2.4 shows that political affiliation is a key driver of sentiment dispersion across consumers. Consistent with the documented switching behavior of sentiment around changes in the presidential party, Democratic consumers tend to be optimistic when a Democrat holds the White House, while Republican consumers are pessimistic (and vice versa). The strength of political affiliation also predicts the degree of optimism (when their preferred party holds the White House) or pessimism (when their party is out of power) reported by consumers. For instance, under the current Biden (D) presidency, strong Democrats are more optimistic than weak Democrats, weak Democrats are more optimistic than weak Republicans, and weak Republicans are more optimistic than strong Republicans. While we continue to use sentiment as a way to summarize household beliefs, this relative ordering can be seen in individual survey questions. For instance, individuals who are strongly aligned with the party in the White House have lower inflation expectations than individuals who are weakly affiliated with the same party or affiliated with the opposing party.

We also show that the explanatory power of political affiliation is increasing: in recent years, a third of the variation in sentiment across households is explained by political affiliation alone; and conditional on political affiliation, additional demographic data explains almost none of the variation. This is a change even from the mid-2000s, when political affiliation could explain about 10% of the variation, while additional demographics could explain another 10%. Further high-frequency analysis around elections where the White

House switches parties confirms our previous results: households affiliated with the party in the White House are more optimistic in the lead-up to the election; this differential degree of optimism is stable up until the election, at which point sentiment falls immediately in the days following the outcome of the election. Our high-frequency analysis also provides novel insights into the dynamics of partisan beliefs during the recent surge in inflation. During this period, the partisan gap in inflation expectations surged to five percentage points (and amongst strong partisans, peaked at seven percentage points). We find that this partisan gap was particularly reactive to CPI releases in the first half of 2021: following each release Republican inflation expectations spike (and economic sentiment declines) relative to Democrats.

To better understand the role of political affiliation in shaping economic beliefs, Section 2.5 explores the reasoning consumers report in surveys when explaining their macroeconomic forecasts or personal financial conditions. We find a striking result: "partisan narratives" (wherein consumers mention government or governmental policies explicitly as a main driver of their economic beliefs) have risen considerably. Both favorable and unfavorable partisan narratives are on the rise; in recent years, it is not uncommon to find that nearly half of consumers justify their economic beliefs by appealing to partisan-based reasoning. This is much higher than what we find before the mid-2000s, when often less than 10% of consumers report partisan narratives as drivers of their economic beliefs.

We confirm that these partisan narratives do affect consumer beliefs: consumers who switch to reporting more negative partisan narratives also tend to become more pessimistic in their economic beliefs (and vice versa). Consistent with our findings above, the pass-through is large when the White House changes parties, and the reaction during presidential elections has grown dramatically over time. Outside of elections, we find modest but non-negligible pass-through of partisan narratives to economic beliefs, which has remained stable over time. Importantly, we continue to utilize high-frequency analysis to study both the dynamics and pass-through of partisan narratives around a number of salient policy events. Perhaps surprisingly, we find that partisan narratives react strongly to many policy events outside of presidential elections. Nonetheless, the pass-through to economic beliefs remains modest but stable in all cases outside of presidential elections.

Consistent with economic theory, the stark differences in economic beliefs we document are also associated with differential economic actions. Section 3 conducts event studies around the 2016 and 2020 presidential elections. For 2016, we combine disaggregated consumption data with voting data at the zip code level to study consumption responses in the weeks surrounding the 2016 election. Section 3.2 finds that areas with a higher Republican vote share exhibited higher consumption in the weeks following the 2016 election of Donald Trump (R). We next utilize high-frequency, individual-level survey responses and actual consumption measures from Democratic and Republican households during the days before and after the 2020 election. The results in Section 3.4 corroborate the evidence from the 2016 election: relative to Democratic households, Republican households became more pessimistic about unemployment, expected higher inflation, and became less enthusiastic about purchasing consumption goods following the 2020 election of Joe Biden (D). Finally, we show that actual consumption of Republican households relative to Democratic households fell following the 2020 election. However, our results suggest that the consumption response to the 2016 election was both economically and statistically stronger than in 2020. While there may be many explanations for this asymmetry, one important difference we find is due to COVID-19. Starting in March 2020, we find markedly different consumption patterns across partisan households; this difference persists up to the 2020 election, which makes interpretations of the 2020 election results more difficult than the 2016 election. Nevertheless, these results show that political polarization plays an important role not just in shaping (reported) economic beliefs, but also in driving actual consumption decisions.

After empirically documenting our five facts about polarized expectations and consumption, Section 4 discusses their implications for theoretical models of expectation formation. We first show that, unsurprisingly, our results are not consistent with full-information rational expectations (FIRE), the canonical model of expectations formation. Next, we discuss a range of commonly used belief formation models which depart in various ways from FIRE (e.g., robustness, rational inattention, learning, and diagnostic expectations). All of these models can partially explain some of the facts. However, we show that none of these models can fully explain all of these facts simultaneously. Therefore, rationalizing the facts presented in this paper requires either combining these approaches or developing new theoretical tools. Section 5 concludes and discusses avenues for future work.

*Literature Review:* The five facts we document are related to a wide range of papers in the literature. Here we discuss the relationship between each of our results and those in existing papers, and highlight the important novel findings which our paper contributes to the literature. Our first fact relates to a number of papers that study the correlation structure between subjective beliefs about different macroeconomic variables (e.g., Carvalho and Nechio 2014, Dräger et al. 2016, and Andre et al. 2022). Like this paper, Kamdar (2019), studies the factor structure of consumer beliefs and finds evidence of dimensionality reduction. Kamdar (2019) emphasizes the relationship between consumers' unemployment and inflation forecasts, and how this correlation differs from both the data and from professional forecasters (see also Bhandari et al. 2022). The novel insight of our results here is the remarkable stability of factor structures across all subgroups of consumers, *including* political affiliation. This result is surprising, particularly when viewed through the lens of theoretical models of information acquisition which try to account for persistent belief heterogeneity (e.g., Sims 2003, Sims 2010, and Kőszegi and Matějka 2020).[2] In these models, long-run belief dispersion arises from how agents learn about the economy, which in turn implies fundamentally different factor structures across these groups. Instead, we find that conditional on being "optimistic" or "pessimistic," both Democrats and Republicans make nearly identical macroeconomic and financial forecasts.

Our second fact confirms the findings of a number of papers which study the dynamics of consumer beliefs. Similar to Benhabib and Spiegel (2019), Mian et al. (2021), and Gerber and Huber (2009), our results stress the importance of presidential elections in affecting economic beliefs (see also Gillitzer and Prasad (2018) for evidence in the context of Australian elections). Relative to these papers, we focus on within-household beliefs and therefore have much more precise estimates of the *persistence* of beliefs before and after presidential elections. Combined with our first fact, our results emphasize the quantitative importance of the "persistence breakdown" we document around changes in the White House. Additionally, our use of high-frequency survey data around these elections improves identification relative to existing work. In particular, our paper confirms that it is the outcome of the election itself which immediately shifts economic beliefs (and not policy changes or policy pronouncements following the election during "lame duck" Congressional or Presidential sessions, or policy enacted following the inauguration of the new administration).

In addition to the papers discussed above, a large literature starting with Bartels (2002) highlights the role of political affiliation over time in shaping subjective assessments of economic policies, macroeconomic conditions, or objective facts more generally (e.g., Ladner and Wlezien 2007, Jerit and Barabas 2012, Alesina et al. 2018, Bertrand and Kamenica 2018, Alesina et al. 2020, Levy 2021, Gillitzer et al. 2021, and Bursztyn et al. 2023). Our third fact confirms and extends these results. Like these papers, we find that the explanatory power of political affiliation has only continued to rise. We expand these findings to account for strength of political affiliation, and taken together with our first fact, we stress the quantitative importance of this result. A novel result of our paper is that in recent years, political affiliation is far and away the strongest predictor of economic beliefs: other demographic information adds essentially no predictive power (previous work has found demographics such as age or gender predict economic beliefs; e.g., Bruine de Bruin et al. 2010, Bryan and Venkatu 2001, and Malmendier and Nagel 2016). Our results are particularly striking in the recent period of high inflation, where we find a massive gap in inflation expectations of over seven percentage points amongst strong partisans. Here also another novel insight of our

[2] Also see Levy and Razin (2019) for a survey of the literature on "echo chambers."

paper is the sharpened identification provided by high-frequency analysis.

Fact four is broadly related to a growing literature on subjective narratives. Papers such as Bénabou et al. (2018), Shiller (2017), Shiller (2020), and Andre et al. (2023) directly examine the subjective reasoning reported by individuals. While our fourth fact is related to these papers, to our knowledge our findings regarding both the dynamics of partisan narratives as well as the pass-through of partisan narratives to economic beliefs are new. Our results on partisan narratives confirm the importance of the presidency in shaping consumer beliefs. But perhaps surprisingly, we also find that partisan narratives are strongly reactive to other political events as well. Here, our high-frequency analysis of partisan narratives and beliefs around salient political events sheds some light on the mechanisms behind our findings. In general it is difficult to distinguish between cases where partisan policy actions cause consumers to update their economic beliefs, and cases where consumers become more pessimistic and retroactively blame partisan policies. Our high-frequency analysis shows that following certain salient policy events, the causal chain starts with policy shocks, which in turn leads to changing subjective narratives, and finally to shifts in economic beliefs.[3]

Our fifth fact relates to a few papers which study consumption responses to elections. Mian et al. (2021) find that presidential elections have no effect on household spending. On the other hand, some have found a positive effect in low-frequency consumption in large regions associated with the winning party. Gerber and Huber (2009) use county-level quarterly taxable sales to show that consumption responds differently following a presidential election based on the political composition of the county. Benhabib and Spiegel (2019) use quarterly data to show that sentiment, when instrumented with state-level political outcomes, is predictive of state-level income growth. In Australia, Gillitzer and Prasad (2018) use monthly automobile purchase data to show that elections affect economic beliefs and spending. Our findings support the view that political affiliation also affects household consumption. Relative to existing papers, our measures of consumption are based on high-frequency, individual-level data. Our consumption measure is largely composed of non-durable or semi-durable consumption; thus, while we do not observe the entire reaction of spending to electoral outcomes, we focus on a slice of consumption which can be adjusted more quickly. However, while our consumption results are clear following the 2016 election, our results are more ambiguous in 2020.[4]

[3] Although not directly related, there are also a number of papers which study theoretically and empirically the role of media bias in shaping partisan beliefs. For instance, see Mullainathan and Shleifer (2005), Gentzkow and Shapiro (2010), Larcinese et al. (2011), Martin and Yurukoglu (2017), and DellaVigna and Kaplan (2007).

[4] Although not the focus of our paper, our results here also relate to papers such as Allcott et al. (2020) which examine the differential partisan reactions to COVID-19.

Our consumption results are more broadly related to the literature which documents the role of political affiliation in shaping economic actions. For instance, a recent series of papers find that political affiliation influences portfolio choices of individuals and institutional investors (e.g., Bonaparte et al. 2017, Meeuwis et al. 2022, and Cassidy and Vorsatz 2021). Furthermore, bankers and credit rating analysts affiliated with the party in control of the White House have been shown to give cheaper loans and higher ratings (Dagostino et al. 2020 and Kempf and Tsoutsoura 2021). Firm managers have been shown to be more optimistic about earnings forecasts when their preferred party holds the presidency (Stuart et al. 2021) and accordingly invest more (Rice 2020).

More broadly, our paper is related to the literature which uses surveys to examine beliefs. The recent Handbook of Economic Expectations (Bachmann et al. 2022) reviews the use of surveys to measure expectations of consumers, firms, and professionals in a wide range of settings including consumption, savings, education and housing (in particular, see D'Acunto et al. 2023, Kuchler et al. 2023, and Carstensen and Bachmann 2023). We also relate to papers which study empirically the link between reported beliefs and economic actions. Existing empirical work establishing this relationship has found mixed results, but taken as a whole suggest a relationship (see D'Acunto et al. 2023 for a review). For example, inflation expectations have been shown to affect household spending and investment decisions, but the magnitude and direction of the relationship has varied across environments and individuals studied. For instance, Bachmann et al. (2015) and Galashin et al. (2020) find that expectations play a small role in driving actual decisions. Our results are in line with the bulk of recent papers such as Armantier et al. (2015), Roth and Wohlfart (2020), D'Acunto et al. (2022), Coibion et al. (2019a), Roth and Wohlfart (2020), and Coibion et al. (2019b) which find strong links between expectations and economic decisions.

# 2 Expectations and Polarization

This section uses survey data to provide empirical evidence that political affiliation plays an important and increasingly influential role in how individuals form their economic beliefs.

## 2.1 Data

We use the Michigan Survey of Consumers (MSC) to measure consumer beliefs, which has been conducted monthly since 1978. The MSC is a rotating panel: every month, approximately 500 to 600 consumers are surveyed, about 40% of whom are selected from the pool of respondents surveyed six months prior. Prior to 2018, consumers are surveyed at most twice, but since 2018 some respondents are surveyed a third time. Most of our analysis focuses on variation in consumer beliefs at the monthly frequency; however, we conduct additional analysis at the daily frequency using the exact interview date at which a consumer was surveyed. Interview dates were taken from the Inter-University Consortium for Political and Social Research (ICPSR).

The MSC asks a variety of questions about consumer beliefs. Broadly speaking, the survey asks consumers their views on either aggregate economic conditions or personal financial conditions. Some of these questions are backwards-looking, while others are forwards-looking. The questions about beliefs in the MSC typically solicit a categorical response from the consumer. The consumer frequently is given a range of possible responses, which fall broadly into an "optimistic" response, a "stay the same/neutral" response, and a "pessimistic" response. For instance, the MSC obtains unemployment expectations by asking "How about people out of work during the coming 12 months - do you think that there will be more unemployment than now, about the same, or less?" Similarly, expectations about ones' own personal financial conditions are obtained with "And 5 years from now, do you expect that you (and your family living there) will be better off financially, worse off financially, or just about the same as now?" Using a similar format, the MSC asks respondents for their current attitude towards consumption. Respondents can answer that it is a good, fair, or bad time to buy household durables, cars, and homes. Most of the MSC questions follow the same categorical pattern above; however, there are a handful of questions which ask for quantitative responses. In particular, households are asked to report their inflation expectations and personal income growth expectations in terms of percent changes.

Furthermore, the MSC asks some open-ended questions that allow respondents to provide reasons for their views. Following questions about recent business conditions, current personal financial conditions, and consumption attitudes, respondents are asked "Why do you say so?" and can give up to two reasons. The MSC then codes the given reasons into approximately 100 categories. Categories include macroeconomic reasons (such as the level of prices, interest rates, firm profitability, or recession), personal reasons (such as changes in pay, debt, or asset positions), and other miscellaneous reasons (such as pollution and crime or changes in family composition).

Lastly, the MSC collects demographic information such as income and education from the survey respondents. Furthermore, in recent years, the MSC has solicited respondents' political leaning as well as the strength of that affiliation. Political affiliation was collected for at least 3 months of the year since 2006; however, prior to 2006 the question was only fielded a handful of times in the early 1980s. In most recent surveys, the political affiliation question has been framed as "Generally speaking, do you usually think of yourself as a

Republican, a Democrat, an Independent or what?" If the respondent says "Democrat" or "Republican", they are then asked if their affiliation is strong or not so strong, whereas if the respondent says "Independent" or something else, they are then asked if they think of themselves as being closer to the Republican, Democratic party, or neither.

As a point of comparison, we also use the Survey of Professional Forecasters (SPF). The SPF is a rotating panel survey that began in 1968. The survey is conducted quarterly and in recent iterations has included approximately 40 respondents. These professionals are individuals who make forecasts as a primary function of their jobs, including forecasters at banks, chief economists at trade organizations, or academics who research forecasting methods. Respondents report their numerical forecasts for a variety of macroeconomic and financial variables, including inflation, unemployment, GDP, and interest rates.[5]

## 2.2 Factor Structure of Consumer Beliefs

We first estimate the factor structure of survey-based consumer beliefs. The purpose of this analysis is threefold. First, understanding the degree of dimension reduction in consumer beliefs is informative in and of itself. Second, we examine the factor structure of beliefs both over time and across different groups of consumers. This gives insights into the drivers of belief heterogeneity, and can help distinguish heterogeneity arising from differences in the factors compared to differences in the underlying factor structure. Finally and most concretely, the factor analysis in this section provides a more parsimonious "summary statistic" description of beliefs, which we utilize in the remainder of the paper.

Recall that the majority of MSC questions are categorical rather than continuous. Accordingly, for our factor analysis of the MSC, we utilize multiple correspondence analysis (MCA), the categorical analog to a principal components analysis. In our baseline specification, we estimate the factor structure of all MSC questions which have been asked continuously since 1978, excluding: (i) current consumption buying attitudes; and (ii) beliefs about government policy (as these are used in other parts of our analyses). This leaves us with eleven questions regarding both forward- and backward-looking beliefs about aggregate and personal economic and financial conditions. Two questions are backward-looking over the previous year (personal financial conditions and aggregate business conditions). Eight questions are forward-looking over the next year (expectations of household nominal income, household real income, personal financial conditions, aggregate unemployment, interest rates, inflation, relative business conditions, and overall business conditions). The final question we include asks respondents for their forecast of aggregate business conditions over the next

[5] Appendix B provides additional details for this and all other data sources used in this paper.

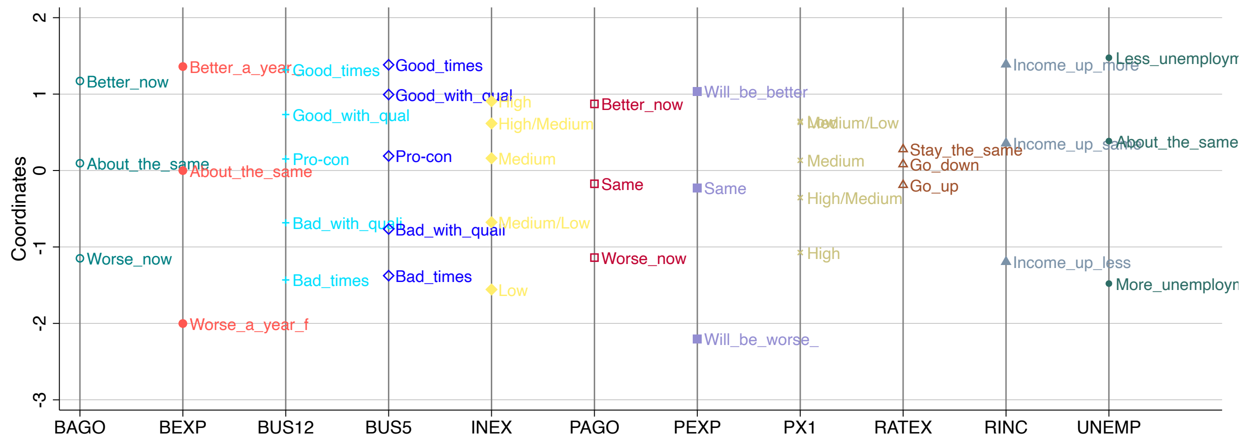


Figure 1: MCA Loadings, First Component

Notes: each point represents the estimated loadings of the first component for a given categorical response in the baseline MCA. The include questions are: business conditions better or worse from a year ago (BAGO), business conditions in one year relative to now (BEXP), business conditions over the next year (BUS12), business conditions over the next 5 years (BUS5), family income over the next year (INEX), personal financial condition relative to a year ago (PAGO), personal financial condition in one year (PEXP), inflation over the next year (PX1), interest rates over the next year (RATEX), family real income over the next one to two years (RINC), unemployment over the next year (UNEMP). Quantitative questions (PX1 and INEX) are binned into quintiles.

five years. Responses are categorical, except for the questions regarding price and income expectations. Hence, to include these in the MCA we bin these responses into quintiles.[6]

We find that the first component alone explains the overwhelming majority of the variation in beliefs. The first component explains 79% of the variation, while the second component explains only an additional 7%. Figure 1 reports the loadings associated with the first factor of the MCA, which gives us insight into the economic interpretation of the first component. We see that the loadings are monotonically increasing as one moves from the pessimistic responses to the more optimistic responses for all questions. For example, take the question on unemployment expectations over the next year. Respondents can answer that unemployment will go up (pessimistic), stay the same (neutral), or go down (optimistic). The pessimistic response that unemployment will increase has a negative coefficient. The neutral response that unemployment will stay the same has a loading near zero. Lastly, the optimistic response of unemployment falling enters the first component with a positive loading. This pattern is repeated for nearly every question (including inflation, to the extent that consumers view rising prices as a negative outcome). The only slight exception is the question regarding interest rates. However, while the other responses can be unambiguously mapped to optimistic, neutral, and pessimistic responses, the change in interest rates is ambiguous (e.g., borrowers may react differently than savers to an increase in interest rates).

[6] Additional information for all questions used in our MCA analyses are described in Appendix B.

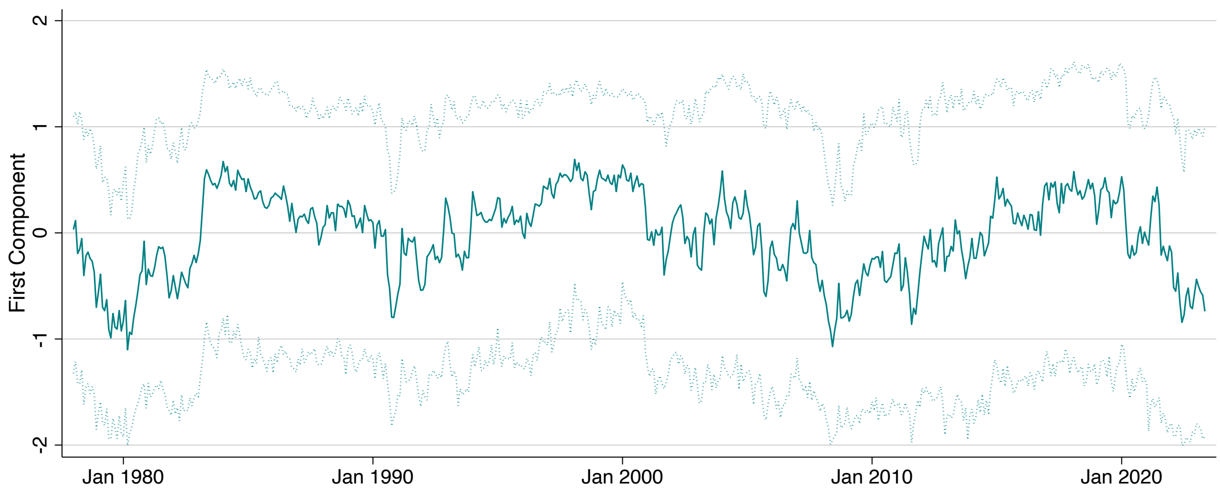


Figure 2: Sentiment Distribution Across Time

Notes: time series of the first component $f_{i,t}$ from the baseline MCA analysis. The solid line is the median value of sentiment, while the dotted lines are the 90-10 percent distribution.

Therefore, we interpret the first component as a general measure of the sentiment of the consumer as in previous work (also see Kamdar 2019). However, while we call this measure "sentiment," none of our analysis hinges on this precise interpretation of the first component. Moreover, we do not take a stand on if sentiment is based on rational or irrational reasoning, as doing so is unnecessary for our takeaways. The key point is that the first component explains the majority of variation in consumer beliefs and thus can be used as a summary statistic for a wide range of consumer beliefs.

From our baseline MCA, we construct the fitted first component $f_{i,t}$ for each individual $i$ across time $t$. From Figure 1, we see that a high level of $f_{i,t}$ is associated with more "optimistic" responses to any of the questions included in the MCA. We use this measure to study the dynamics of consumer beliefs. Using this summary statistic is reasonable given that it explains a large majority of the variation in beliefs. And on a practical level, using a summary statistic allows us to present succinct analyses rather than investigating each survey question independently.

Figure 2 shows how the distribution of sentiment $f_{i,t}$ across individuals has evolved over time. The solid line is the median economic sentiment across individuals in a given month. As expected, this measure is related to the business cycle, falling during recessions and increasing during booms. However, the dotted lines (plotting the 90-10 percent distribution) show that there is substantial variation in sentiment across individuals at any given time, and even during large booms and busts (by construction, the standard deviation of the fitted component $f_{i,t}$ is equal to one). For instance, during the 2009 recession, more than 10% of individuals exhibited positive economic sentiment. To get a sense of the magnitude of the heterogeneity in sentiment at any given point in time, notice that the difference between the 90-10 percentiles is larger than movements in median sentiment around booms and busts.

Both the estimated loadings as well as the factor structure in the baseline MCA are robust to a variety of specifications. First, the results are robust to using different sets of questions in the MCA, as shown in Panel A of Table 1. Columns 2 through 6 report MCA results for various alternative questions. Regardless of whether we only include aggregate questions (columns 2 and 3), only include questions about personal conditions (columns 4 and 5), or only use backwards looking questions (column 6), the first component explains the majority of the variation in beliefs. Furthermore, the fitted first components are highly correlated across specifications.

Next, Panels B, C, and D of Table 1 report MCA results using the baseline questions across different subgroups of individuals. Panel B divides individuals into six groups depending on their highest level of education. Panel C investigates the top and bottom quintiles of income, home value, and stock market investments. Panel D divides individuals by political affiliation. For all subgroups, the first component explains the majority of the variation of beliefs. In all cases, the correlation of our baseline sentiment measure and the fitted first components from subgroup estimates are essentially one. The extremely strong correlations of the fitted first components suggest that the estimated loadings, regardless of the subgroup that the MCA is estimated on, are very similar (Appendix Figure A2 examines the correlation of the loadings directly). Put another way, the mapping of economic beliefs to sentiment (or vice versa) is similar across all subgroups. Regardless of demographic background (including political affiliation), "optimistic" consumers expect lower inflation, expect lower unemployment, expect stronger business conditions, report improved business conditions over the past year, report improvements in their own personal financial conditions over the past year, and so on.

Finally, the factor structure of consumer beliefs is very stable over time as well. Rather than conducting a single MCA over the whole sample, we instead estimated rolling MCAs over short (six month) windows. We find very similar results to the pooled MCA (see Appendix Figure A1).

**Fact 1: Household beliefs follow a single factor ("sentiment") model. The mapping between sentiment and beliefs is similar across all demographic groups (including political affiliation).**

Table 1 summarizes our first fact: the majority of variation in household beliefs can be captured by a single factor model and, regardless of demographic subgroup, the mappings

Table 1: MCA Fraction Explained

| **Panel A:** | Baseline | Aggregate | | Personal | | Past |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| % Explained (Dim 1) | 78.8 | 87.4 | 76.4 | 80.7 | 63.8 | 85.2 |
| % Explained (Dim 2) | 7.1 | 3.4 | 4.5 | 14.3 | 13.1 | 14.8 |
| Baseline Corr. | | 0.923 | 0.914 | 0.690 | 0.731 | 0.679 |
| Obs. | 215,899 | 240,381 | 136,122 | 267,797 | 72,450 | 305,708 |
| Start Date | 1978 | 1978 | 1990 | 1978 | 2007 | 1978 |
| **Panel B:** | Education | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| % Explained (Dim 1) | 75.2 | 77.0 | 79.4 | 80.1 | 77.8 | 75.1 |
| % Explained (Dim 2) | 11.0 | 7.8 | 6.9 | 6.4 | 7.3 | 8.9 |
| Baseline Corr. | 0.997 | 0.998 | 0.999 | 0.999 | 0.999 | 0.999 |
| Obs. | 4,836 | 10,416 | 57,200 | 55,022 | 51,404 | 35,387 |
| Start Date | 1978 | 1978 | 1978 | 1978 | 1978 | 1978 |
| **Panel C:** | Income | | Home Value | | Investment | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| % Explained (Dim 1) | 76.9 | 77.7 | 83.6 | 80.7 | 81.2 | 79.8 |
| % Explained (Dim 2) | 8.8 | 7.0 | 5.6 | 6.3 | 5.2 | 6.5 |
| Baseline Corr. | 0.998 | 0.999 | 0.998 | 0.998 | 0.999 | 0.998 |
| Obs. | 25,376 | 51,713 | 11,378 | 15,280 | 12,085 | 15,802 |
| Start Date | 1979 | 1979 | 1990 | 1990 | 1990 | 1990 |
| **Panel D:** | Pol. Aff. (Broad) | | | Pol. Aff. (Strong) | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| % Explained (Dim 1) | 73.3 | 82.2 | 87.3 | 73.2 | 80.5 | 88.9 |
| % Explained (Dim 2) | 7.9 | 5.9 | 4.3 | 7.8 | 7.4 | 4.0 |
| Baseline Corr. | 0.998 | 0.999 | 0.998 | 0.997 | 0.999 | 0.998 |
| Obs. | 24,470 | 20,682 | 23,278 | 10,576 | 5,391 | 8,933 |
| Start Date | 2006 | 2006 | 2006 | 2006 | 2006 | 2006 |

Notes: Panel A reports MCA results for various questions: (1) baseline; (2) aggregate questions only; (3) adds 5-year price/gas price questions (introduced in 1990); (4) personal questions only; (5) adds home price questions (introduced in 2007); (6) backward-looking questions only. Panels B, C, and D report MCA results using the baseline set of questions across different respondent subgroups. Panel B uses different education groups: (1) no high school; (2) some high-school; (3) high-school diploma; (4) some college; (5) college degree; (6) post-grad. Panel C uses the bottom and top quintiles of income groups (1 and 2); home value groups (3 and 4); and investment groups (5 and 6). Panel D uses political affiliation groups: (1) includes all Democrats; (2) all independents; (3) all Republicans; (4) strong Democrats; (5) strict Independents; (6) strong Republicans. The baseline correlation is the correlation of fitted first components of a given MCA and the baseline first component.

between beliefs and sentiment are extremely similar.

In contrast to consumers, professionals have a higher dimension factor structure to their beliefs (in spite of the fact that the SPF only asks about aggregate economic outcomes). The results of a principal component analysis on the SPF are reported in Appendix Table A1. We find that the first factor explains only 34% of the variation in professional beliefs; the second and third factors still explain 19% and 11% (respectively). Furthermore, Appendix Figure A3 shows that there is considerably less heterogeneity in the first component of professional forecasters' beliefs at a given point in time. Instead, time series variation in the median (particularly around booms and busts) are much larger than the 90-10 percentile distribution at any time. Finally, the estimated factor structure varies much more over time (see Appendix Figure A4).[7]

## 2.3 Persistence and Switching Behavior of Beliefs

As seen in Figure 2, at any given time there is wide dispersion across households in optimism and pessimism. Next, we exploit the panel structure of the MSC to explore how sentiment varies over time for a given consumer. Recall that a subset of consumers are selected for follow-up interviews occurring six months after the initial interview date. Thus, for repeat respondents we estimate the following regression:

$$f_{i,t} = \alpha_t + \beta_t f_{i,t-6\text{m}} + \varepsilon_{i,t}. \tag{1}$$

The variable $f_{i,t}$ is the first component from the baseline MCA for an individual $i$ at month $t$. We regress this on the individual's previous response six months prior, $f_{i,t-6\text{m}}$. Hence, the coefficient $\beta_t$ in equation (1) is a measure of the degree of persistence in sentiment over time. We estimate equation (1) using a rolling six-month sample, pooling over individuals.

Panel A of Figure 3 plots the estimated coefficients $\hat{\beta}_t$ at the end of a six-month rolling sample. In general, sentiment is highly persistent: individuals who were optimistic six months prior tend to be optimistic today; similarly, pessimistic individuals remain pessimistic. However, there are some notable exceptions. The shaded regions correspond to the 12-month period following the outcome of presidential elections. In these periods, $f_{i,t}$ is determined by responses given after the outcome of the election, while $f_{i,t-6\text{m}}$ is determined by responses from before the election for at least some of the respondents included in the rolling window. Hence, in the shaded regions equation (1) regresses some responses following

[7] Because the SPF only reports quantitative forecasts, to allow for a more direct comparison we also binned all responses into quintiles in order to conduct a "pseudo-MCA." We find very similar results: the first component explains only 36%, while the second and third components explain 28% and 10% (respectively). Appendix Figure A5 shows similar distributional variation in the first component as Appendix Figure A3.

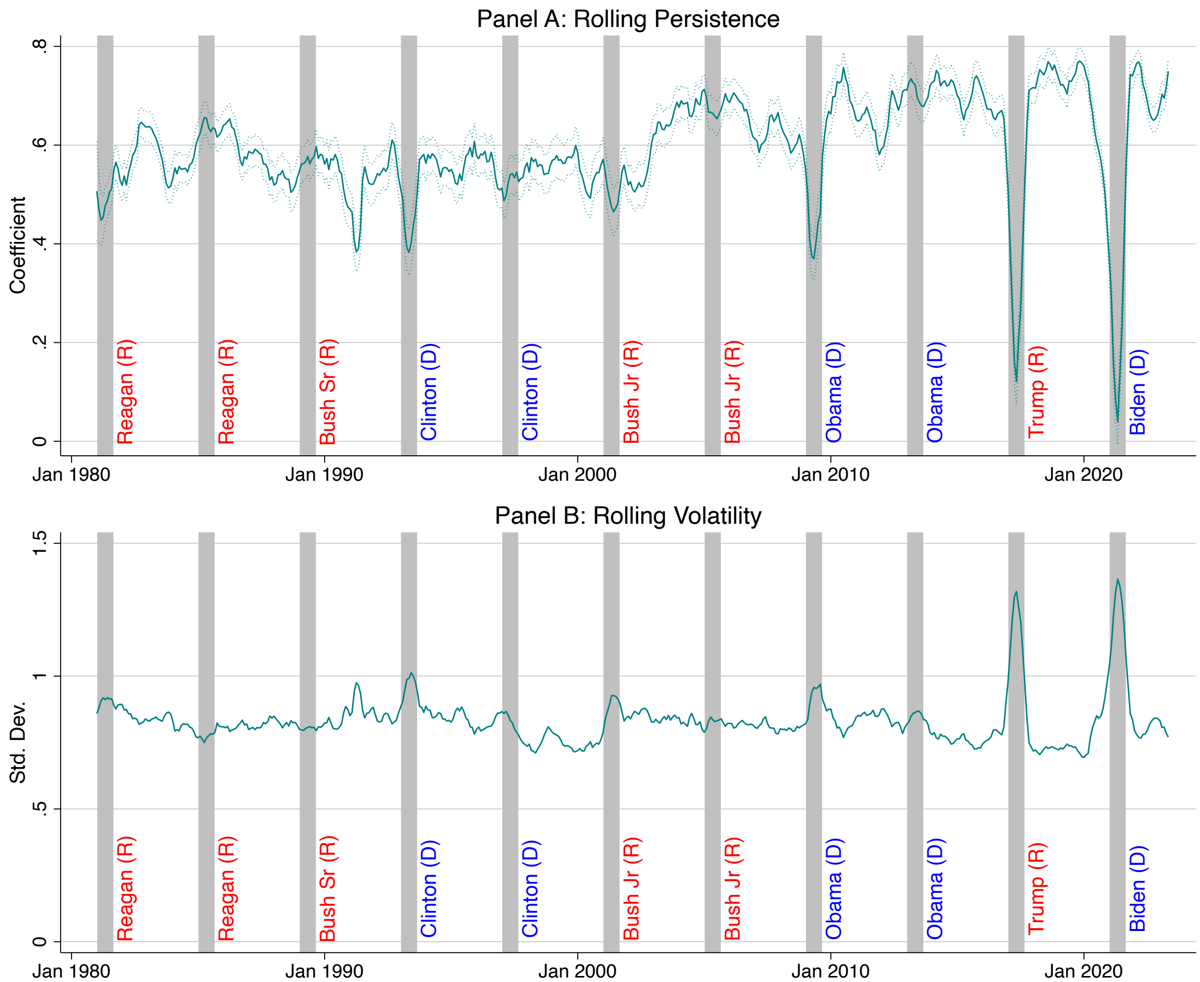


Figure 3: Persistence and Volatility of Sentiment

Notes: Panel A plots the coefficient of six-month rolling window regressions pooled across respondents $f_{i,t} = \alpha_t + \beta_t f_{i,t-6\text{m}} + \varepsilon_{i,t}$ where $f_{i,t}$ is the first component from the baseline MCA analysis. Panel B plots the standard deviation of $f_{i,t} - f_{i,t-6\text{m}}$ over six-month rolling windows. Shaded regions correspond to 12-month periods following presidential elections. Dotted lines represent 90% confidence intervals.

an election on the same individual's responses that were given before the election.

We see that it is only during certain presidential elections when sentiment persistence breaks down. These elections where the persistence falls are exactly the elections where the White House changed party: 1980, when Reagan (R) replaced Carter (D); 1992, when Clinton (D) replaced Bush Sr. (R); 2000, when Bush Jr. (R) replaced Clinton; 2008, when Obama (D) replaced Bush Jr., 2016, when Trump (R) replaced Obama; and 2020, when Biden (D) replaced Trump. Notice that the switching behavior of beliefs does not occur when the same party stays in the White House (for example, the 1988 election where the White House when from Reagan (R) to Bush Sr. (R) or the 2012 re-election of Obama (D)).

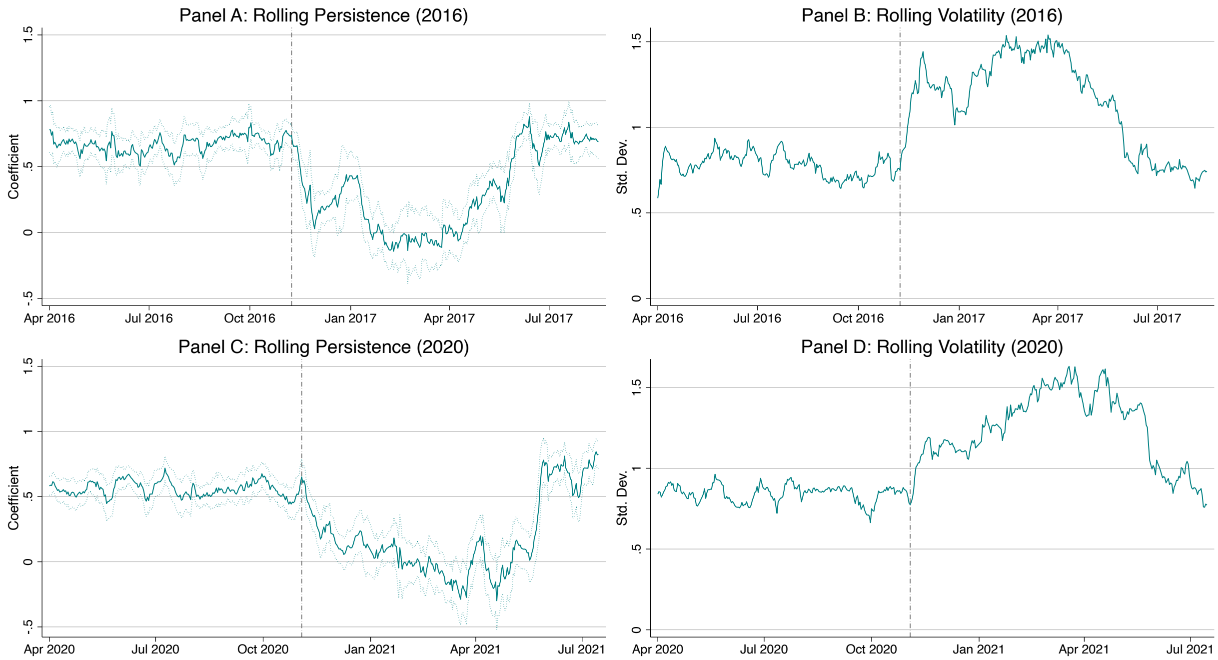


Figure 4: Daily Persistence and Volatility of Sentiment

Notes: Panels A and C plot the coefficient of 14-day rolling window regressions pooled across respondents $f_{i,\tau} = \alpha_\tau + \beta_\tau f_{i,\tau-6\text{m}} + \varepsilon_{i,\tau}$ where $f_{i,\tau}$ is the first component from the baseline MCA analysis. Panels B and D plot the standard deviation of $f_{i,\tau} - f_{i,\tau-6\text{m}}$ over 14-day rolling windows. Vertical lines indicate the 2016 and 2020 presidential elections.

We also see some evidence that outside of elections, sentiment persistence has increased over time (with an average $\hat{\beta}_t$ of roughly 0.5 in the first half of the sample, and roughly 0.7 in the second half). Additionally, outside of elections the explanatory power of these persistence regressions has also increased (Appendix Figure A6 reports the $R^2$ of our rolling regressions; the first half of the sample averages roughly 0.3, while it has climbed to 0.4 or 0.5 in the second half). At the same time, the magnitude of the switching behavior following elections has also increased over time. The drop in sentiment persistence in the 2016 and 2020 elections are the most striking, where the estimated coefficient $\hat{\beta}_t$ actually turns negative.

Panel B of Figure 3 plots the standard deviation of $f_{i,t} - f_{i,t-6\text{m}}$ over six-month rolling windows. This difference measures the change in sentiment for individual $i$. As shown in Panel B, volatility of sentiment changes is typically stable. However, precisely when persistence deteriorates, volatility rises. Following a presidential election where the party in the White House changes, volatility of beliefs rise. Note that this increase in volatility is not apparent when examining the *level* of sentiment $f_{i,t}$ across individuals (as in Figure 2); instead, it is the change in sentiment within a given individual that becomes more volatile.

The drop in persistence and rise in volatility of beliefs following presidential elections is immediate. We utilize the exact dates each survey was taken to sharpen our findings. We amend equation (1) slightly and estimate the following regression: $f_{i,\tau} = \alpha_\tau + \beta_\tau f_{i,\tau-6\mathrm{m}} + \varepsilon_{i,\tau}$, where we use $\tau$ to denote the day each survey was taken, rather than the month $t$. Figure 4 repeats the analysis of Figure 3, but narrows to a 14-day rolling window and focuses on the months surrounding the 2016 and 2020 election. Panels A and C plot the estimated persistence coefficient $\hat{\beta}_\tau$ surrounding the 2016 and 2020 elections (respectively). Panels B and D plot the standard deviation of $f_{i,\tau} - f_{i,\tau-6\mathrm{m}}$ over 14-day rolling windows surrounding the 2016 and 2020 elections. We find that the drop in persistence and the rise in volatility immediately follows the election. The changes last approximately six months. Recall that follow-up surveys occur six months after the initial survey, so during this period $f_{i,\tau}$ is estimated from the responses of individual $i$ after the election, while $f_{i,\tau-6\mathrm{m}}$ is from responses before the election.[8]

**Fact 2: Sentiment persistence falls when the White House changes party. The magnitude of this switching behavior has risen over time.**

We have now documented our second fact: household sentiment is highly persistent during almost all periods; however, there are progressively larger breakdowns of sentiment persistence following presidential elections when the White House switches parties (but not during other presidential elections, or midterm elections).

For robustness, Appendix Figures A8 and A9 show the same pattern for two individual questions in the MSC (business conditions and unemployment). We estimate the probability that individuals answer optimistically or pessimistically conditional on the response that they gave when they were surveyed six months prior using a multinomial logit model around the 2016 and 2020 elections. The results show that usually beliefs tend to be unchanged. However, following the elections where the White House switches party, beliefs are most likely to switch.

In contrast to households, the persistence and volatility of the first component of professional forecasters beliefs are stable through elections, even when the White House switches parties (Appendix Figures A10, A11, A12 and A13). As expected, the volatility of beliefs are more related to the business cycle, with big spikes during recessions.

[8]Appendix Figure A7 presents the analogous charts for previous elections. While the changes are smaller in earlier elections, there still is an immediate drop in persistence and increase in volatility following an election when the incumbent presidential party lost. There are no notable changes in persistence or volatility if the incumbent presidential party wins the election.

## 2.4 Political Affiliation and Beliefs

We now turn to examining the role that political affiliation plays in driving the heterogeneity in consumer sentiment $f_{i,t}$ found above. Using the MSC question on political affiliation (available with sufficient frequency since 2006), we show that a respondent's political affiliation is strongly related to their economic beliefs and overall sentiment. We estimate the following rolling regression:

$$f_{i,t} = \alpha_t + \gamma_t \cdot \mathbf{1}\{i = \text{Republican}\} + \varepsilon_{i,t}. \tag{2}$$

We estimate equation (2) on a sample of individuals who identify as either Republicans or Democrats only (using a six-month rolling window). Hence, $\hat{\gamma}_t$ represents the average level of sentiment for Republican consumers relative to Democratic consumers. Panel A of Figure 5 shows strong evidence of differential levels of sentiment between the two political parties. Consistent with our results in Section 2.3, sentiment tends to switch from pessimistic (optimistic) to optimistic (pessimistic) when the occupant of the White House switches towards (away from) an individual's preferred party. Democratic households were relatively less optimistic when Bush Jr. (R) was in the White House, became more optimistic when Obama (D) was elected in 2008, became more pessimistic when Trump (R) was elected in 2016, and became more optimistic when Biden (D) was elected in 2020. On the other hand, Republicans were relatively optimistic with Bush Jr., more pessimistic when Obama was elected, more optimistic when Trump was elected, and more pessimistic when Biden was elected.

Panel B replaces the independent variable in equation (2) with $\mathbb{E}_{i,t}[\pi_{t+12}]$, the respondent's one-year-ahead inflation expectations. Inflation expectations also show strong differences across parties. In particular, households affiliated with the party in the White House have lower inflation expectations. This finding is particularly striking following the 2020 election, when Republican consumer inflation expectations averaged nearly five percentage points higher than those of Democratic consumers.

Next we investigate the differential sentiment and inflation expectations by strength of party affiliation. Over rolling six-month windows, we regress sentiment (Panel C) and inflation expectations (Panel D) on dummy variables for strong Republicans (solid red line); weak Republicans (dashed red line); Independents who lean Republican (dotted red line); Independents who do not lean towards either party (dashed black line); Independents who lean Democratic (dotted blue line); weak Democrats (dashed blue line); and strong Democrats (solid blue line). Since no constant is included in the regression, the estimated coefficients are simply the average for each given subgroup. A clear pattern emerges: the stronger the affili-


Figure 5: Differential Sentiment and Expected Inflation

Notes: Panel A plots the coefficient from regressing $f_{i,t}$ (sentiment from the baseline MCA) on an indicator for Republican using a six-month rolling window and a sample of only Republicans and Democrats. Panel C plots the coefficient from regressing $f_{i,t}$ on indicators for disaggregated political affiliation using a six-month rolling window. Panel E plots the $R^2$ of regressing $f_{i,t}$ on political affiliation dummies only and the marginal addition of adding several other demographic variables. Panels B, D, and F replicate the analyses for inflation expectations $\mathbb{E}_{i,t}[\pi_{t+12\text{m}}]$. Dotted lines in Panels A and B represent 90% confidence intervals.

ation to the Republican (Democratic) party, the more optimistic and the lower the inflation expectations one is when the Republican (Democratic) party holds the White House.

Furthermore, political affiliation explains a large and increasing fraction of the variation in consumer beliefs. Panels E and F of Figure 5 plot the $R^2$ from the regressions in Panels C and D. For economic sentiment (Panel E) we find an $R^2$ of between 0.1 and 0.2 in the naughts, rising to over 0.3 more recently. When additional demographic variables are included (sex, marital status, education, age, age-squared), in the early part of the sample

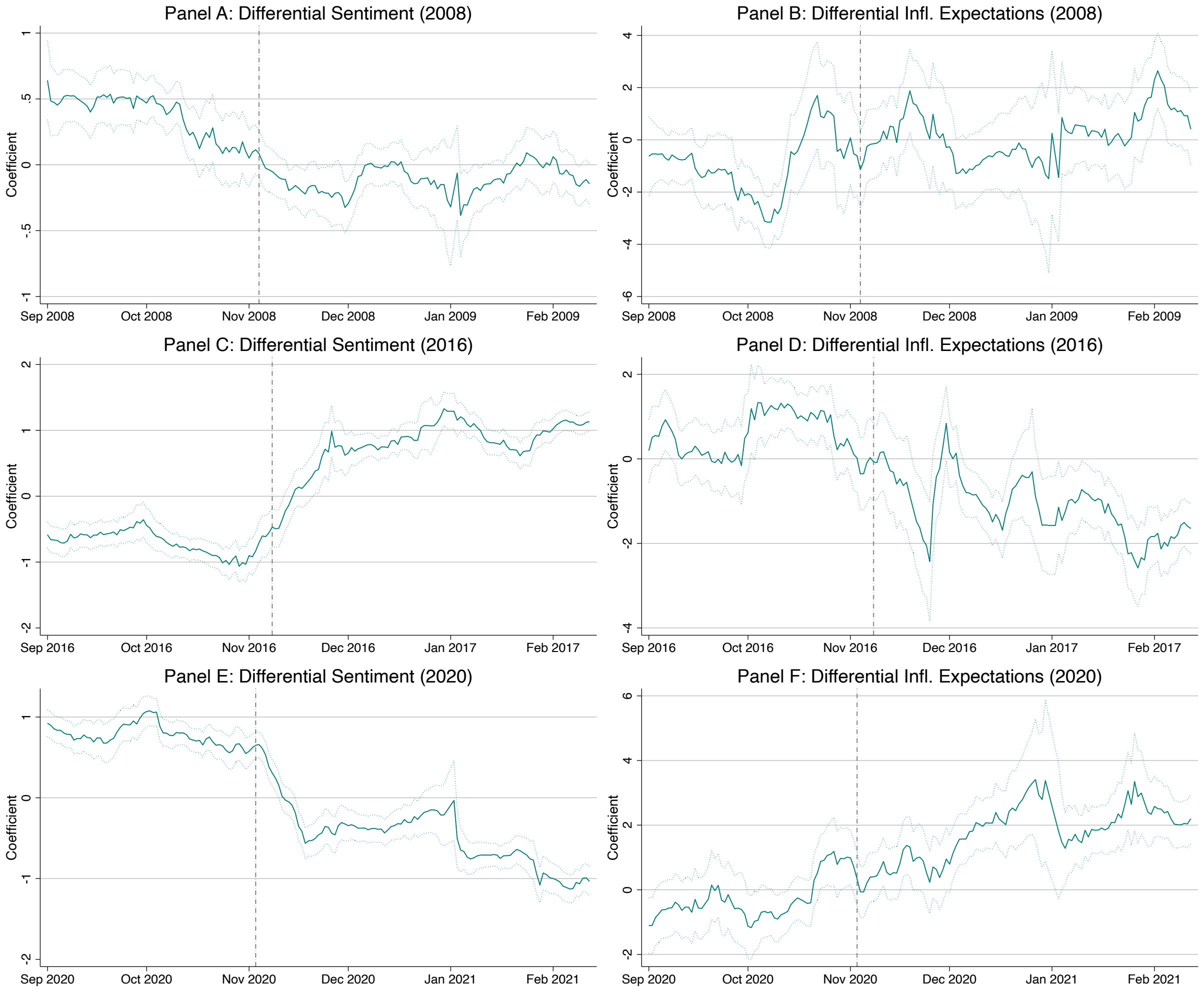


Figure 6: Daily Differential Sentiment and Expected Inflation

Notes: Panels A, C, and E plot the coefficient from regressing $f_{i,\tau}$ (sentiment from the baseline MCA) on an indicator for Republican using a 14-day rolling window and a sample of only Republicans and Democrats. Panels B, D, and F replicate the analyses for inflation expectations $\mathbb{E}_{i,t}[\pi_{t+12\mathrm{m}}]$. Vertical lines indicate the 2008, 2016, and 2020 presidential elections.

the $R^2$ increased modestly. However, in recent years the $R^2$ is virtually unchanged when additional demographic variables are included. Panel F shows the same pattern for inflation expectations (though the overall explanatory power is much lower).

Using the daily MSC data, we zoom in on recent elections to assess if the differential effects occur immediately following elections. Figure 6 plots the estimated coefficient from regressing sentiment or expected inflation on a dummy variable for Republican on a sample of Republicans and Democrats over a 14-day rolling sample. Due to the small samples, these results are noisier than the previous monthly analyses. Panels A and B report results surrounding the 2008 election of Obama. We see evidence of an immediate relative decrease

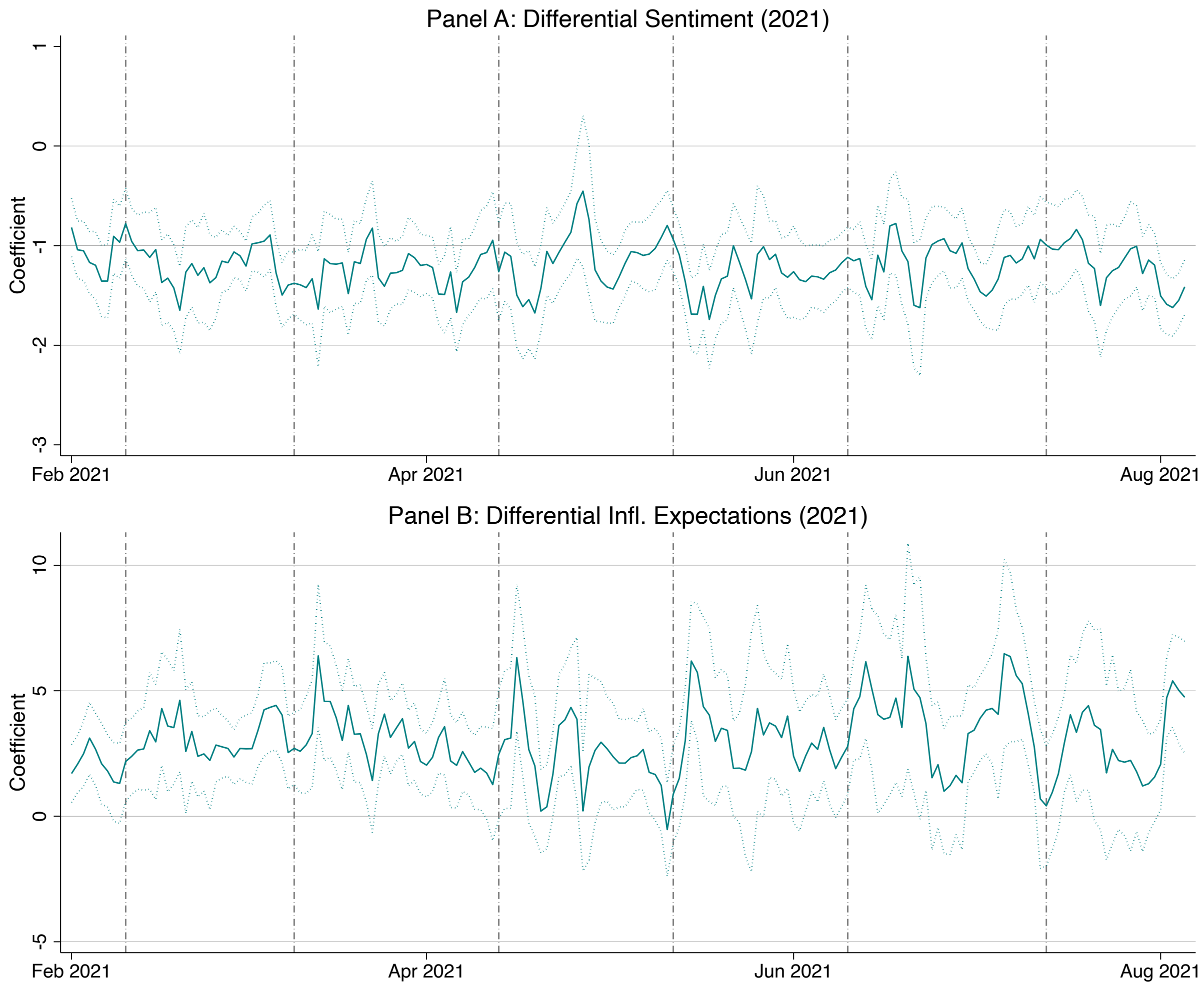


Figure 7: Daily Differential Sentiment and Expected Inflation, 2021

Notes: same regression coefficients as described in Figure 6, but using a four-day rolling window across the first half of 2021. Vertical lines indicate the release dates of CPI reports.

of sentiment and increase of inflation expectations for Republicans relative to Democrats, but the estimated magnitudes are not large or always statistically significant. Panels C and D report results surrounding the 2016 election of Trump. Here we see a large and significant differential increase in Republican sentiment. There is also a relative decrease in inflation expectations of Republicans. Finally, Panels E and F present the results surrounding the 2020 election of Biden. Once again, we see that immediately following the election, Republican sentiment falls and inflation expectations rise (relative to Democratic beliefs).

Given the sharp partisan movements in sentiment and inflation expectations observed in Figure 5 following the 2020 election and throughout the initial spike in inflation during 2021, we further explore the high-frequency movements in beliefs over this period. Figure 7 repeats our analysis from Figure 6, zoomed in on the first half of 2021. Here we use much smaller (four-day) rolling windows in order to better ascertain the high-frequency dynamics of partisan beliefs; of course, the downside of such small windows is that we reduce our sample size and introduce noise into our estimates.[9] Panel A reports rolling regression coefficients for sentiment, while Panel B reports results for inflation expectations. At this high frequency, we see interesting intra-monthly dynamics of Republican beliefs relative to Democrats. We overlay these coefficients with vertical lines denoting the monthly release of CPI reports. Although there is substantial noise in our estimates, a clear pattern emerges: following each CPI release, Republicans increase their inflation expectations (relative to Democrats). Republican sentiment also typically falls (relative to Democrats) following the CPI release dates, although the magnitude is smaller than the response of inflation.

**Fact 3: Political affiliation is an increasingly strong predictor of sentiment.**

We have now shown that sentiment is strongly correlated with political affiliation. Consumers are more optimistic when their preferred party is elected and holds the presidency. When the incumbent party loses a presidential election, there is an immediate switch in sentiment: optimists become pessimists and vice versa. Moreover, closer ties to a political party result in larger changes in beliefs. This is true not only for sentiment (our summary statistic for all beliefs, as shown in Section 2.2), but also inflation expectations.

## 2.5 Partisan Narratives

Our results thus far show clear evidence that consumer beliefs vary along party lines. A natural question is the following: do respondents themselves state that there are partisan-related reasons for their responses? The MSC gathers respondents' reasoning for a subset of questions which allows us to address this question. In particular, after asking respondents about their perceptions regarding business conditions, personal financial conditions, and attitudes towards buying household durables, cars, and homes, respondents are asked the open-ended question "Why do you say so?" For each of the follow-up open-ended questions, respondents can give one or two reasons (or can choose to give no reason). Responses are coded by the MSC into a wide variety of favorable or unfavorable categories (roughly 100 possible categories). Categories include macroeconomic reasons (such as the level of prices, interest rates, firm profitability, or recession), personal reasons (such as changes in pay, debt, or asset positions), and other miscellaneous reasons (such as pollution and

[9]With 14-day rolling windows, we have between $\approx 150 - 300$ Democratic and Republican respondents used in each estimate. With four-day rolling windows, this falls to between $\approx 35 - 100$ Democratic and Republican respondents for each estimate.

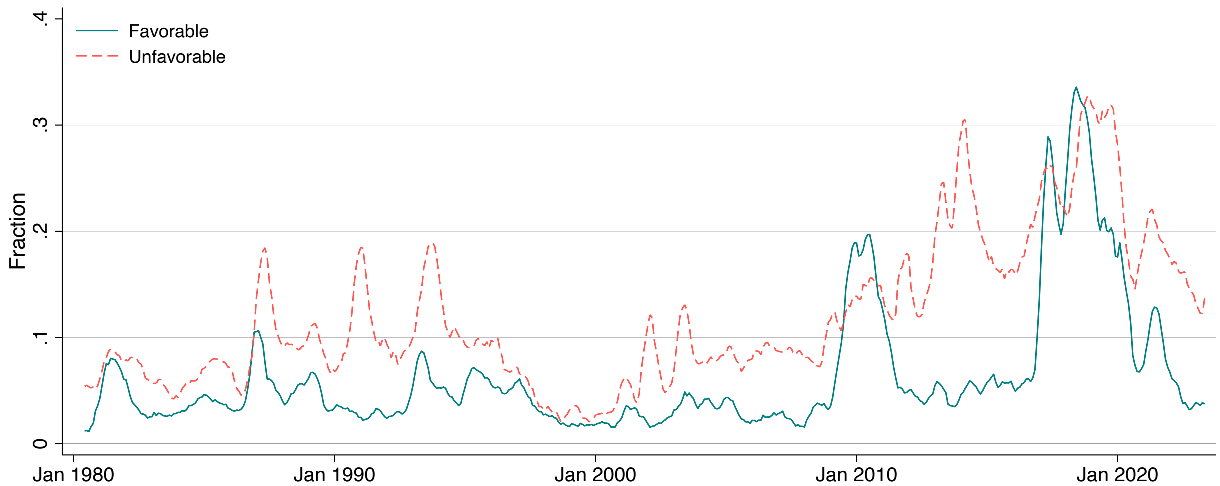


Figure 8: Time Series of Partisan Reasoning

Notes: fraction of respondents over a six-month rolling window who give a favorable or unfavorable government-related reason in any of the narrative questions in the MSC.

crime or changes in family composition). We code each possible reason as "partisan" if the response category includes any references to government-related reasoning. We then create an favorable indicator which is equal to one if a respondent gives a favorable partisan response to any of the narrative questions. Analogously, we create an indicator which is equal to one if the respondent gives any unfavorable partisan-related reason in any of the narrative questions. Note that because there are multiple open-ended questions, it is possible for both indicators to be equal to one. Of course, both indicators can be equal to zero if the respondent gives no partisan-related reason to any of the open-ended questions.[10]

Figure 8 plots the time series of the fraction of responses that gave favorable or unfavorable partisan narratives to any of the open-ended questions. We see that there has been a marked increase in both favorable and unfavorable partisan narratives. Although there was some fluctuation in the late 1980s and early 1990s (particularly for unfavorable partisan narratives), on average well under 20% of respondents typically gave any partisan narratives as a main driver of their economic beliefs. However, over the last decade we see that individuals are increasingly likely to give partisan-based reasons for their expectations. On average, over 20% of respondents hold unfavorable partisan-based narratives; while the

[10]Note that we do not consider narrative responses about interest rates as "partisan" (despite the fact that these responses are related to Federal Reserve policy). For our analysis, we include all open-ended narrative-based MSC responses which have been asked continuously since the early 1980s. Starting in 1992, there was a narrative question added to the survey on home *selling* attitudes; in order to extend our analysis as far back as possible, we exclude this question from our analyses. Appendix B provides precise details for how we categorize open-ended responses.

fraction of individuals with favorable partisan narratives is more volatile, this frequently rises to or above 20% as well in recent years.

Next, we study how the rise of partisan narratives reasoning has affected economic beliefs and sentiment. In order to construct a simple numerical measure of partisan narratives, we first denote the difference of the favorable indicator and unfavorable indicator as $g_{i,t}$; hence $g_{i,t} = 1$ if individual $i$ in month $t$ gave only favorable partisan-based reasoning, $g_{i,t} = -1$ if instead agent $i$ gave only unfavorable partisan-based reasoning; and $g_{i,t} = 0$ if agent $i$ either gave no partisan-based reasoning, or gave both favorable and unfavorable narratives. Then we assess pass-through of partisan narratives to sentiment with the following regression:

$$\Delta f_{i,t} = \alpha_t + \beta_t \Delta g_{i,t} + \varepsilon_{i,t}, \tag{3}$$

where $\Delta f_{i,t} = f_{i,t} - f_{i,t-6\text{m}}$ is the change in sentiment from Section 2.2. The dependent variable $\Delta g_{i,t} = g_{i,t} - g_{i,t-6\text{m}}$ is the change in the quantitative partisan narrative measure for individual $i$ relative to their responses six months prior. Positive values indicate that a consumer has become more favorable (or less unfavorable) in the reported partisan narratives, while negative values indicate more unfavorable (or less favorable) partisan reasoning.[11]

Panel A of Figure 9 plots estimated coefficients from rolling regressions using six-month windows. We find that an increase in favorability of an individual's partisan narratives (or a decrease in unfavorable partisan narratives) increases sentiment. While this estimate is significantly different from zero, usually the effect is modest. For instance, our estimates imply that a consumer who switches from neutral to unfavorable partisan narratives ($\Delta g_{i,t} = -1$) will report a decline in sentiment of approximately $\Delta f_{i,t} \approx -0.25$ (where recall that by construction, $f_{i,t}$ has a standard deviation of one). The major exception is presidential elections, where we find partisan reasoning strongly affects sentiment. This is particularly true in the most recent elections. Overall, while there has been a rise of partisan reasoning, the pass-through to sentiment is largely stable outside of elections.

We confirm these results using an alternative approach. The MSC asks question about government policy: "As to the economic policy of the government – I mean steps taken to fight inflation or unemployment – would you say the government is doing a good job, only fair, or poor job?" We code these responses as one, zero, and negative one (respectively). Let $\Delta \tilde{g}_{i,t}$ indicate the change in government favorability of individual $i$ between time $t$ and six months prior. Panel B of Figure 9 estimates equation (3) replacing $\Delta g_{i,t}$ with $\Delta \tilde{g}_{i,t}$. If an individual reports an improvement in favorability of government policy, we once again find

[11] This is a parsimonious linear specification, but qualitatively our results are the same if we allow for non-linearities between favorable and unfavorable partisan narratives. Appendix Figure A14 reports these results.

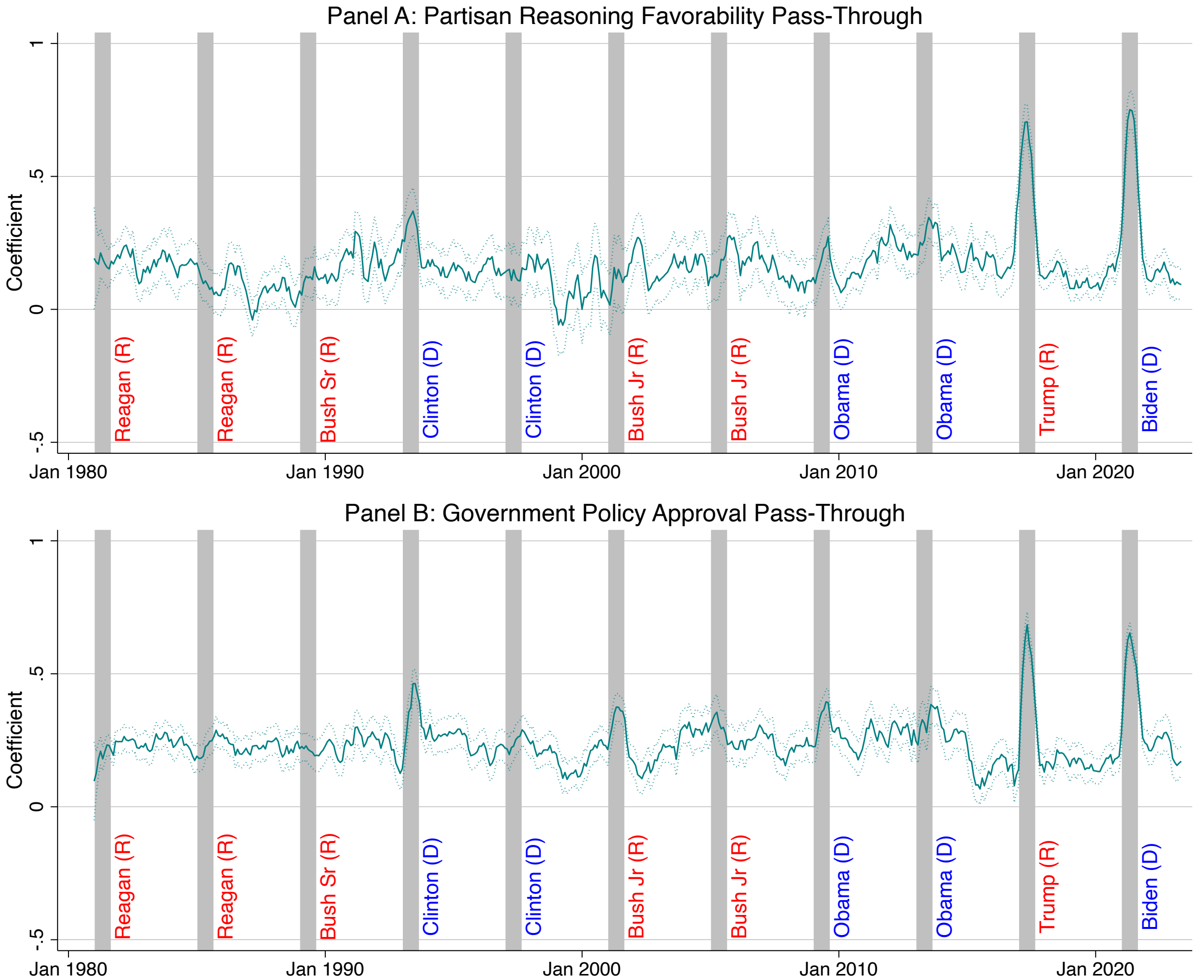


Figure 9: Partisan Reasoning Pass-Through to Sentiment

Notes: Panel A uses a six-month rolling window and plots the coefficient of $\Delta f_{i,t} = \alpha_t + \beta_t \Delta g_{i,t} + \varepsilon_{i,t}$ where $g_{i,t}$ is the difference in indicators for favorability and unfavorability. Panel B replicates this analyses using the change in government policy approval, $\Delta \tilde{g}_{i,t}$, as the independent variable. Shaded regions correspond to 12-month periods following presidential elections.

a modest but significant positive correlation with sentiment. Quantitatively, our estimates are very similar to Panel A: an increase in government favorability is associated with a decline in sentiment by approximately a quarter of a standard deviation. Additionally, the pass-through is largely stable outside of elections. During these times when the White House changes parties (in particular the last two elections), we see a major increase in our estimated pass-through of government favorability to sentiment.

Figure 9 might seem to suggest that as consumers become more focused on presidential elections, they ignore other policy events. However, using daily MSC data around various major policy events, we show that this is far from the case. In Figure 10, we examine the


Figure 10: Partisan Reasoning and Pass-Through during Policy Events

Notes: Panels A, C, and E plot the fraction of respondents over a 14-day rolling window that give a favorable or unfavorable government-related reason in any of the narrative questions in the MSC. Panels B, D, and F use 14-day rolling windows and plot the coefficient of $\Delta f_{i,\tau} = \alpha_\tau + \beta_\tau \Delta g_{i,\tau} + \varepsilon_{i,\tau}$ where $g_{i,\tau}$ is the difference in indicators for favorability and unfavorability using a six-month rolling window. Vertical lines indicate the start of cash for clunkers (July 24, 2009), a debt ceiling suspension (July 31, 2011), and the Trump tax cuts (January 1, 2018).

dynamics of partisan narratives and the pass-through to sentiment during three major policy events: the Car Allowance Rebate System of 2009 ("cash for clunkers"); the Budget Control Act of 2011 ("2011 debt ceiling crisis"); and the Tax Cuts and Jobs Act of 2018 ("Trump tax cuts"'). Panels A, C, and E show that partisan reasoning (either favorable or unfavorable) reacts sharply at the start of cash for clunkers, the 2011 debt ceiling suspension, and the Trump tax cuts (respectively). These reactions occur in the days immediately following major policy events, suggesting that consumers are quite attentive to these non-election partisan events. But consistent with our results at the monthly frequency, Panels B, D, and

F show that even at these times of large shifts in partisan reasoning, the effect on sentiment is stable.[12]

**Fact 4: Partisan reasoning has risen, but the pass-through to sentiment is modest and stable outside of presidential elections.**

Consistent with our findings in Sections 2.3 and 2.4, partisan narratives react more and more strongly to changes in the White House. This is also associated with an overall increase in the degree of partisan narratives (both favorable and unfavorable). Moreover, partisan reasoning is highly reactive to many major policy events beyond presidential elections. However, while changes in partisan reasoning affects consumers' economic beliefs, these effects are modest and have remained stable throughout the entire sample. The most recent elections are the only exceptions, where shifts in partisan narratives are associated with large swings in sentiment.

# 3 Consumption and Polarization

Standard economic theory implies a tight connection between agents' beliefs and actions. Hence, the results in Section 2 suggest that political shocks should lead to large changes in consumption. In this section, we explore whether political affiliation also plays a role in how individuals make spending decisions in response to presidential elections.

As a first step, we continue to utilize survey responses in the MSC. We assess how Republican and Democratic households differ in their attitudes towards purchases over time. We conduct a MCA utilizing three consumption-related questions which ask respondents for their attitudes towards purchasing household durables, cars, or houses. As with most MSC questions, respondents give categorical responses: good, fair, or bad time to buy. Like in our baseline MCA results on consumer expectations, the first component explains roughly 80% of the variation in consumption attitudes.[13]

Figure 11 plots the estimated coefficients from a rolling regression of consumption attitudes on political affiliation using six-month windows. The dependent variable is the first component of the consumption MCA. In Panel A, the independent variable is a dummy for

[12]Appendix Figures A15 and A16 plot the daily time series for partisan reasoning and pass-through to sentiment for a variety of other policy events and the two most recent elections. Policy events are associated with increases in partisan reasoning, yet the pass-through to sentiment is stable. For the 2016 election, there is an immediate and large increase in unfavorable reasoning and the pass-through to sentiment also rises. For the 2020 election, partisan reasoning reacts modestly, but our estimated pass-through to sentiment rises significantly.

[13]Appendix Figures A17, A18, and A19 provide the loadings for the first component, how much of the variation in consumption beliefs is explained by the first component, and the relationship to our measure of sentiment.

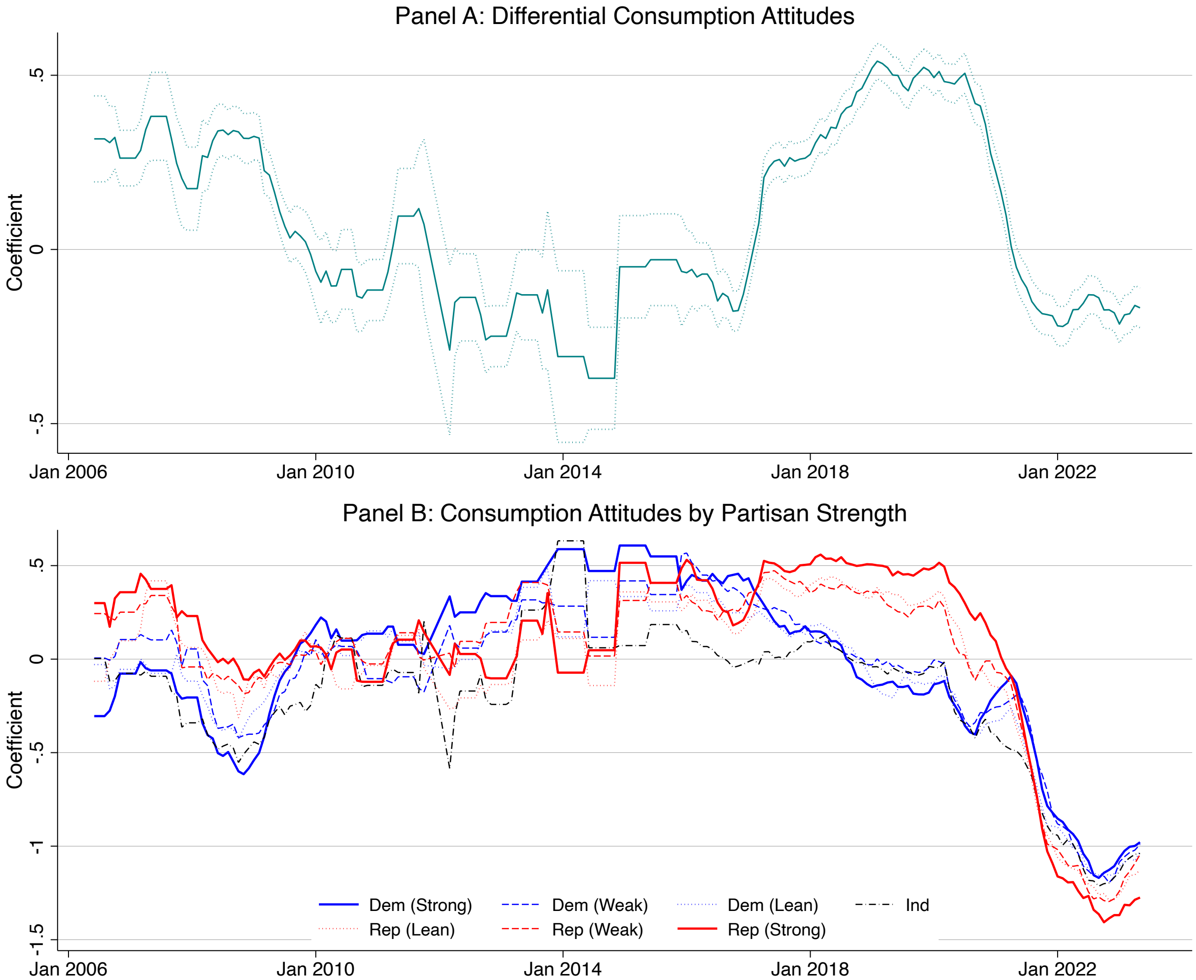


Figure 11: Consumption Attitudes by Political Affiliation

Notes: Panel A plots the coefficient from regressing $h_{i,t}$ (the first component of an MCA with consumption-related questions on MSC data) on an indicator for Republican using a six-month rolling window and a sample of only Republicans and Democrats. Panel B plots the coefficient from regressing $h_{i,t}$ on indicators for disaggregated political affiliation using a six-month rolling window.

whether the household reports they are Republican, restricting the sample to include only Republicans and Democrats. Hence, the estimated coefficient reports how much more optimistic or pessimistic Republican households are relative to Democratic households towards purchasing different goods. In Panel B, a range of political affiliation dummy variables are included (ranging from strong Democrat to strong Republican, as in Figure 5). The estimated coefficients indicate the average level of consumption optimism or pessimism of each subgroup across time.

While the results are not as stark as for economic expectations, the same pattern emerges again. During periods in which a Republican is in the White House, Republicans relative to Democrats tend to feel that it is a better time to purchase durables, cars, and homes. This pattern flips during periods in which a Democrat occupies the White House. Republican households were more likely to say it was a good time to buy durables, homes, and cars relative to Democratic households during the presidencies of Bush Jr. (2000-2008) and Donald Trump (2016-2020). In contrast, Republican households were less likely to say it was a good time to make purchases relative to Democratic households during the presidencies of Obama (2008-2016) and Biden (2020-). Furthermore, the strength of consumer political affiliation is correlated with the strength of consumption optimism (when their preferred party controls the White House) or consumption pessimism (when the opposition controls the White House).

However, the Michigan Survey is an imperfect tool for studying the behavior of consumption as it only asks about consumption *attitudes* but does not solicit or measure actual consumption patterns. Instead, we now use the 2016 and 2020 elections as case studies. For the 2016 election, we utilize high frequency spending data combined with voting data at the zip code level to examine how political affiliation affects spending decisions. For the 2020 election, we again utilize high frequency spending data but are able to match this spending data to individual-level measures of political affiliation. Our results provide novel insights into how changes in economic expectations affect actual consumption and interact with political affiliation.

## 3.1 2016 Case Study: Data

We use the Nielsen Homescan data to study the response of consumption and spending to the outcome of the 2016 and 2020 presidential elections.[14] Nielsen Homescan is a panel dataset which measures U.S. consumer behavior. Panelists use scanners to record all purchases of products tracked by Nielsen in food and non-food categories. The dataset tracks when, where, and how much of each product a given panelist purchases across time. Nielsen also records demographic and geographical information on the panelists. Since 2007, the Homescan data includes roughly 60,000 households.

Nielsen Homescan does not include political affiliation of its panelists. Thus, in order to proxy for political affiliation, we merge our consumption data with voting data. Our voting data is from the United States Election Project at the University of Florida, which has collected precinct-level data for elections since 2016. The 2016 data includes all 50 states

[14] Researcher(s)' own analyses calculated (or derived) based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researcher(s) and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

and the District of Columbia. Voting data is recorded at the precinct level, which is not observed in the Homescan dataset (and in general is not a common geographical unit of measure outside of elections). The most disaggregated geographical data in the Nielsen data is the five-digit zip code, and so we use geographical shape data to allocate precinct-level voting data to zip codes. Precincts are smaller geographical areas than zip codes, and most precincts fall entirely within zip codes. For precincts that fall within multiple zip codes, we allocate votes proportionally to each zip code based on geographical size overlap. For each zip code, we calculate the Trump margin of victory as the percentage point difference between the vote share for Trump and Clinton (excluding third party votes from the vote share calculation).[15]

In our baseline analysis, we use the Nielsen Homescan data to construct weekly measures of consumption spending at the five-digit zip code level. Although in principle we could conduct our analysis at the daily frequency, at such a high frequency consumption is quite lumpy. Since presidential elections fall on Tuesdays, our weekly measure starts on Wednesday and runs through the following Tuesday. Our baseline analysis focuses on zip codes with at least 100 votes. Combined with the Nielsen spending data, this leaves us with about 17,000 zip codes. The median number of votes across zip codes in our sample is roughly 5,000, with the largest made up of about 42,000 votes. The median Republican margin across zip codes in our sample was roughly 21% in favor of Trump. The largest vote margins in our sample range from 94% in favor of Trump, to 97% in favor of Clinton.

Although the Nielsen Homescan data is quite extensive in its coverage of U.S. consumption, it is important to note that the data is not meant to be representative of consumption at the zip code level. Because our source of variation in strength of political affiliation is at the zip code level, we collapse our data to this level of aggregation. However, in robustness exercises we also conduct our analysis using consumption at the more disaggregated household-level.

[15] Panel A of Appendix Figure A20 plots a histogram of the Trump margin in all U.S. zip codes in our data. The distribution is skewed to the right as there were many small zip codes that voted in favor of Trump, despite Clinton winning the popular vote. As a precise example of our zip code voting data, Panel B plots the vote shares by zip code in Orange County, California. Orange County voted for Clinton by a margin of 8.6 percentage points, but as the map shows this does not imply that votes were uniformly distributed across zip codes. Indeed, there are some zip codes that voted strongly in favor of Trump even though the county as a whole voted for Clinton. This highlights the high degree of heterogeneity of political affiliation, even within relatively small geographical units, and emphasizes the importance of using as small a geographic area as possible.

### 3.2 2016 Case Study: Event Study Results

In order to assess how spending reacted to the 2016 election, we estimate the following event study regression:

$$c_{z,t,y} = \alpha_{z,t} + \gamma_{t,y} + \sum_{k=-\underline{T}}^{\overline{T}} \beta_{k,y} \cdot v_z^{16} \cdot \mathbf{1}\{t = k\} + \varepsilon_{z,t,y}. \tag{4}$$

The variable $v_z^{16}$ measures the Trump margin in zip code $z$ in the 2016 election. The outcome variable $c_{z,t,y}$ is (log) consumption in zip code $z$ at week $t$ and year $y$. In order to control for potentially different time trends in consumption across zip codes, we not only include consumption data from 2016, but also from 2014 and 2015 (results are robust to including different years). We normalize the event time $t$ such that $t = 0$ is the week in which the 2016 presidential election took place (where the week is defined to begin the day after the election). We set $\underline{T} = \overline{T} = 7$ in order to study consumption patterns two months before and after the election. $\overline{T} = 7$ corresponds to the end of the year; in robustness exercises, we combine additional consumption data from 2017 and find similar results. For years without a presidential election, we set $t = 0$ to correspond to the week in which a hypothetical election would have taken place. The regression equation (4) also includes zip code and time fixed effects. Hence, the coefficient $\beta_{k,2016}$ represents the predicted percentage increase in consumption in a zip code with 1 percentage point higher Trump margin $k$ weeks following the 2016 election.

Figure 12 plots the estimated $\hat{\beta}_{k,2016}$ from the event study in equation (4). The increase in consumption is large and statistically significant at the 10% level in the weeks immediately following the election. In contrast, the estimates for the weeks preceding the election are smaller and not significantly different from zero (except for three weeks before the election which is marginally significant). This shows there was no differential time variation in consumption patterns related to voting propensities in the lead-up to the election.

While the standard errors are large, the point estimate remains above zero for all of the weeks in the sample period following the election. Economically, our estimates are also non-trivial: a zip code with 1 percentage point higher Republican margin is associated with about a 0.05 percent increase in consumption over the weeks following the election. To put this in perspective, consider two hypothetical zip codes: in the first, the margin was -50% in favor of Clinton, while the second was 50% for Trump. Then the hypothetical Trump-supporting zip code is predicted to have 5% higher consumption relative to the hypothetical Clinton-supporting zip code in response to the election outcome.

Note that our specification controls for the possibility of predictable time variation in

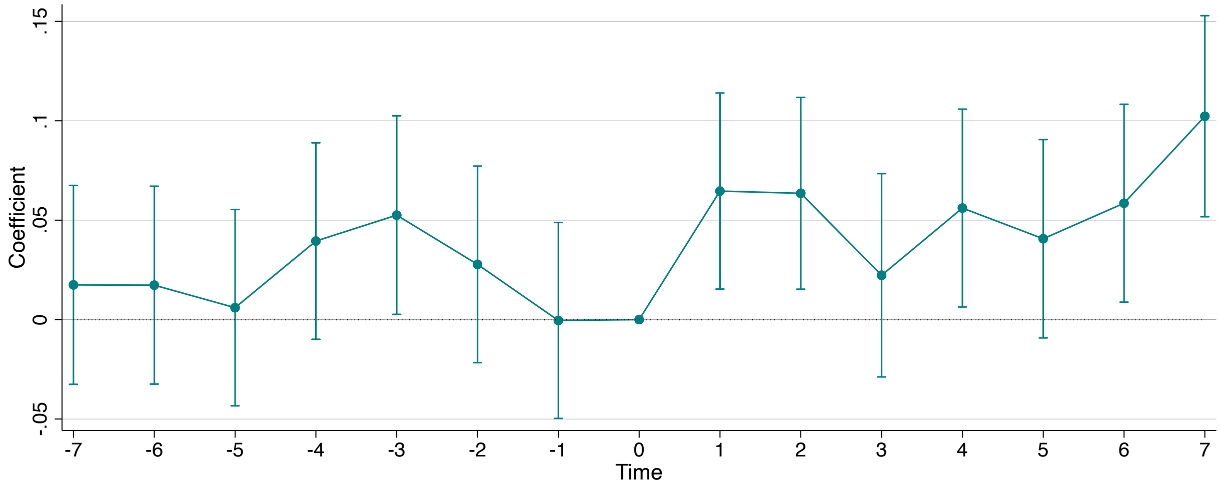


Figure 12: 2016 Event Study of Consumption

Notes: $\hat{\beta}_{k,2016}$ from event study described in equation (4) in the weeks preceding and following the 2016 presidential election. Vertical lines represent 90% confidence intervals. Standard errors are clustered at the zip code level.

consumption for zip codes that tended to favor Trump relative to Clinton. This is not outside the realm of possibility, as we might expect consumption behavior to differ around the holidays given the demographic differences across zip codes. To assess this further, Appendix Figure A21 plots the same event study but only using specific years (2014 through 2017). Besides 2016, no presidential election took place during these years. The results show that there is no differential consumption pattern during the weeks of October and November, but there does appear to be some seasonal differences at the end of the year. However, if anything these patterns suggest that Trump zip codes reduce consumption relative to Clinton zip codes at the end of the calendar year. Finally, focusing on the results using only 2016 data (Panel C), we see that the results are very similar to our baseline regression. None of the other years exhibit the same pattern observed around the 2016 election. Further, the point estimates are never as large as the estimates we find following the 2016 election. This allows us to rule out that our results are driven by differential consumption patterns over time in zip codes that have a higher propensity to vote Republican for reasons unrelated to political shocks (e.g. different seasonal patterns in consumption).

These findings are robust to many other alternative specifications. In order to summarize our robustness exercises more concisely, we amend specification (4) by replacing our event time dummies with a simple post-election dummy:

$$c_{z,t,y} = \alpha_{z,t} + \gamma_{t,y} + \phi_{0,y} \cdot v_z^{16} + \phi_{1,y} \cdot v_z^{16} \cdot \mathbf{1}\{t > 0\} + \varepsilon_{z,t,y}. \quad (5)$$

Table 2: 2016 Event Study Robustness

| **Panel A:** | Base Year 2014 | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Coeff. | 0.040*** | 0.037*** | 0.039*** | 0.041*** | 0.121*** | 0.017 |
| | (0.011) | (0.011) | (0.011) | (0.011) | (0.045) | (0.039) |
| Obs. | 649,879 | 649,879 | 585,912 | 414,472 | 46,864 | 43,514 |
| Groups | 17,104 | 17,104 | 14,848 | 11,198 | 1,159 | 1,112 |
| $R^2$ | 0.668 | 0.677 | 0.671 | 0.635 | 0.677 | 0.680 |
| $R^2$ (within) | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.002 |
| **Panel B:** | Base Year 2015 | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Coeff. | 0.018* | 0.018* | 0.017 | 0.017 | 0.082* | 0.041 |
| | (0.011) | (0.010) | (0.011) | (0.011) | (0.043) | (0.037) |
| Obs. | 432,971 | 432,971 | 390,779 | 275,756 | 31,180 | 28,963 |
| Groups | 16,394 | 16,394 | 14,400 | 10,652 | 1,129 | 1,075 |
| $R^2$ | 0.694 | 0.703 | 0.698 | 0.662 | 0.709 | 0.706 |
| $R^2$ (within) | 0.001 | 0.001 | 0.001 | 0.000 | 0.001 | 0.002 |
| **Panel C:** | 2016 Only | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Coeff. | 0.013* | 0.014** | 0.018** | 0.014** | 0.090*** | 0.043* |
| | (0.007) | (0.007) | (0.007) | (0.007) | (0.029) | (0.024) |
| Obs. | 217,580 | 217,580 | 196,458 | 138,704 | 15,611 | 14,634 |
| Groups | 15,462 | 15,462 | 13,772 | 9,953 | 1,086 | 1,025 |
| $R^2$ | 0.725 | 0.734 | 0.731 | 0.694 | 0.741 | 0.742 |
| $R^2$ (within) | 0.011 | 0.011 | 0.012 | 0.009 | 0.011 | 0.009 |

Notes: $\hat{\phi}_{1,2016}$ from the event study described in equation (5) in the weeks preceding and following the 2016 presidential election. Column (1): baseline sample and data as in Figure 12; column (2): winsorized spending at the 1% and 99% levels; column (3): zip codes with at least 1,000 votes; column (4): zip codes with vote margins at least 25% in favor of either candidate; column (5): California only; column (6): Texas only. Panel A includes data from 2014-2016. Panel B only includes 2015 and 2016. Panel C only includes 2016. Standard errors (in parentheses) are clustered at the zip code level. $***$, $**$, $*$ denote statistical significance at 1, 5, and 10 percent.

As before, we allow for the possibility of differential seasonal consumption patterns by including data from years besides 2016, and continue to use a sample which includes seven weeks before and after the election. Thus, the coefficient $\phi_{1,2016}$ represents the predicted percentage increase in consumption in a zip code with 1 percentage point higher Trump margin in the weeks following the 2016 election.

Table 2 reports a wide array of robustness estimates for our zip code 2016 analysis. Each column reports estimates of $\hat{\phi}_{1,2016}$ from various estimates of equation (4). In Panel A, we continue to use data from 2014-2016. Column (1) reports estimates using the same sample and data as our baseline event study estimates in Figure 12. Column (2) winsorizes spending at the 1% and 99% levels. Column (3) restricts the sample to larger zip codes, with at least 1,000 votes. Column (4) restricts the sample to zip codes with large vote margins, with a margin of at least 25% in favor of either candidate. Finally, columns (5) and (6) restrict the sample to zip codes from California or Texas only (respectively). Panel B estimates the same set of robustness exercises, but only utilizes data from 2015 and 2016, while Panel C only includes data from 2016 (and hence does not control for seasonal consumption differences across zip codes). While the magnitude and statistical significance varies somewhat, across all specifications we find a positive and economically meaningful increase of consumption in Trump-supporting zip codes following the 2016 election.

We have thus far focused our analysis on relatively small (two month) windows surrounding the 2016 election. In part this is due to data issues: each year, there is turnover in the panelists in the Nielsen Homescan data. While this is not necessarily a concern, it potentially introduces some noise into our sample. With this caveat in mind, we can use the 2017 Nielsen Homescan data to analyze the dynamics of consumption in a window encompassing the entire year surrounding the 2016 election. Figure 13 reports these results. We utilize the 2017 data in two ways: in Panel A, we continue to aggregate consumption to the zip code level. In Panel B, we instead estimate equation (4) at the household level, restricting the sample to households for which we observe recorded consumption in at least 70% of periods from 2014 through 2017. In order to better visualize the dynamics of consumption over the longer windows, these exercises aggregate our consumption to the bi-weekly (14 day) frequency (though results are similar at the weekly frequency). In both cases, we see that the consumption response which we found in the immediate aftermath of the election continues into the following calendar year (bi-weeks $t \geq 5$ correspond to the 2017 calendar year in Figure 13). However, the evidence from the restricted sample of households in Panel B does suggest a small reversion of consumption to pre-election levels (although point estimates still remain positive and economically meaningful).

We additionally explore the composition of the consumption response to the 2016 election. Although the consumption recorded in Nielsen Homescan is largely composed of non-durables, the data is extremely disaggregated, allowing us to dive more deeply into decomposing the observed response to the 2016 election. While a fully disaggregated compositional breakdown is beyond the scope of this paper, we separately examine durable consumption responses. Nielsen categorizes consumption goods into approximately 120 different groups, which we use to categorize consumption as "durable". Our durable consumption category includes groups such as "Hardware, Tools" "Cookware," Kitchen Gadgets," or "Electronics, Records, Tapes."[16] To be clear, Nielsen consumption data does not include major spend-

[16] Appendix B provides a detailed breakdown of Nielsen product groups.

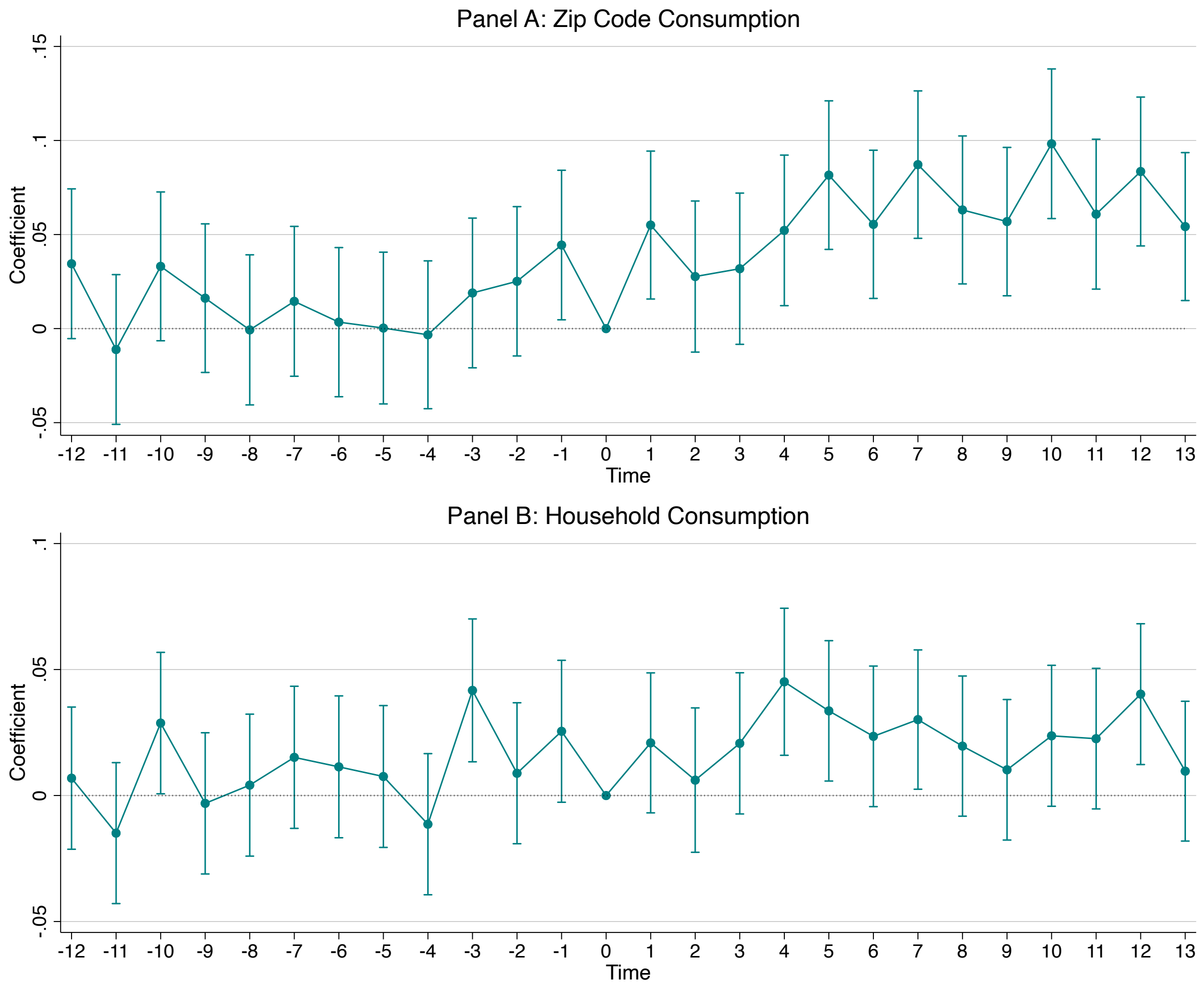


Figure 13: 2016 Event Study of Consumption

Notes: $\hat{\beta}_{k,2016}$ from event study described in equation (4) at the bi-weekly (14 day) frequency. Panel A uses consumption aggregated to the zip code level. Panel B uses household consumption, restricted to households with recorded consumption in at least 70% of periods between 2014 and 2017. Vertical lines represent 90% confidence intervals. Standard errors are clustered at the zip code level (Panel A) or household level (Panel B).

ing categories such as automobile purchases; however, automobile accessories and similar consumption goods are included in our measure of durable consumption.

Because our measure of durable consumption is relatively lumpy, even at the bi-weekly frequency we observe many zeros. Hence, we estimate two versions of equation (5) using durable consumption. The first is simply to replace log consumption with a "log plus one" transformation of durable consumption as our dependent variable. In the second, rather than looking at the (log) level of durable consumption, we use as our dependent variable an indicator which equals one if a household purchased any durable goods within the given

Table 3: 2016 Event Study, Household Durable Consumption

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Coeff. | 0.053*** | 0.006* | 0.079*** | 0.012* | 0.020 | 0.003 |
| | (0.009) | (0.003) | (0.021) | (0.007) | (0.031) | (0.010) |
| Obs. | 529,374 | 529,374 | 112,329 | 112,329 | 336,987 | 336,987 |
| Groups | 62,693 | 62,693 | 12,481 | 12,481 | 12,481 | 12,481 |
| $R^2$ | 0.316 | 0.279 | 0.317 | 0.271 | 0.289 | 0.234 |
| $R^2$ (within) | 0.008 | 0.004 | 0.014 | 0.006 | 0.001 | 0.001 |

Notes: $\hat{\phi}_{1,2016}$ from the event study described in equation (5) using measures of durable consumption only. Column (1): durable consumption transformed using $\log(x+1)$ using all households (2016 only); column (2): durable consumption transformed using $\mathbf{I}\{x>0\}$ using all households (2016 only); columns (3) and (4): same as (1) and (2), but restricted to households with recorded consumption in at least 70% of periods between 2014 and 2017; columns (5) and (6): same as (3) and (4), but additionally including data from 2014 and 2015. Standard errors (in parentheses) are clustered at the household level. $***$, $**$, $*$ denote statistical significance at 1, 5, and 10 percent.

period. Table 3 presents our results across a variety of samples. Column (1) reports the results for the "log plus one" specification, and column (2) reports the indicator specification. In both cases, we use 2016 durable consumption data only, across all Nielsen Homescan panelists. Columns (3) and (4) repeat the analysis, but restrict our sample to only include the set of households described in Figure 13 (Panel B). Columns (5) and (6) continue to use this set of restricted households, but additionally include durable consumption data from 2014 and 2015 (to allow for differential seasonal patterns, as in our baseline event studies). The results here are more ambiguous than our baseline results: while estimates across all specifications are positive, the results are not always strongly significant; in particular, when using our restrictive household sample and controlling for seasonal trends using 2014 and 2015 data, our estimates are smaller and insignificant.

## 3.3 2020 Case Study: Data

We next turn to the recent 2020 presidential election to shed further light on how expectations, consumption plans, and actual consumption react to changes in control of the White House. We utilize a survey of a subset of the panelists in the Nielsen Homescan undertaken by Coibion et al. (2020). The survey was conducted in the days before and after the 2020 presidential election, and solicited responses regarding respondents macroeconomic forecasts (such as inflation and unemployment), as well as attitudes towards consumption decisions (such as buying durables). Importantly, respondents also were asked their political affiliation. Individuals are only surveyed once, and hence we cannot track the beliefs of the same individual before and after the election. However, by comparing the responses of Democratic and Republican individuals over the days preceding and following the election, we can trace out how beliefs and consumption attitudes changed in a high-frequency manner following the results of the election. Furthermore, by linking these responses with the Homescan consumption data, we can compare the actual consumption of Democratic and Republican individuals in the days before and after the election.

Note that unlike most previous presidential elections, the outcome of the 2020 election was not known immediately. The major media organizations did not declare Biden the winner until the weekend following the election.

## 3.4 2020 Case Study: Event Study Results

In order to assess how expectations and consumption plans reacted to the 2020 election, we estimate the following event study regression:

$$y_{i,t} = \gamma_t + \sum_{\kappa=-\underline{T}}^{\overline{T}} \beta_\kappa \cdot \mathbf{1}\{i = \text{Republican}\} \cdot \mathbf{1}\{t = \kappa\} + \varepsilon_{i,t}. \tag{6}$$

The outcome variable $y_{i,t}$ is the response to different questions in the survey (discussed below) for individual $i$ on day $t$. We restrict our analysis to respondents who identify either as supporters of the Democratic or Republican parties. The indicator variable $\mathbf{1}\{i = \text{Republican}\}$ measures whether respondent $i$ is a Republican. As before, we normalize the event time $t$ such that $t = 0$ corresponds to the day in which the 2020 presidential election took place; $\underline{T} = \overline{T} = 12$ captures the full wave of respondents in the 12 days before and after the election. The regression equation (6) also includes time fixed effects. Hence, the coefficient $\beta_\kappa$ represents the predicted differential response to a given question for a Republican respondent during the lead up and aftermath of the 2020 election. Note that unlike equation (4), we only observe these responses in the two weeks before and after the 2020 election and hence cannot include data from other years.

Panels A and B of Figure 14 plot the event study for 12-month unemployment expectations and 12-month inflation expectations, respectively. The results show that before the 2020 election, there was no differential movement in macroeconomic expectations across Republican and Democratic individuals. However, in the days following the 2020 election, Republican respondents began increasing their forecasts of both unemployment and inflation relative to Democratic respondents. Note that the estimates begin increasing the day after the election, and continue increasing until four days following the election, when major media organizations called the election for Biden. The differential increase in Republicans' expectations was roughly five percentage points for unemployment expectations and three percentage points for inflation expectations. These results are consistent with our findings

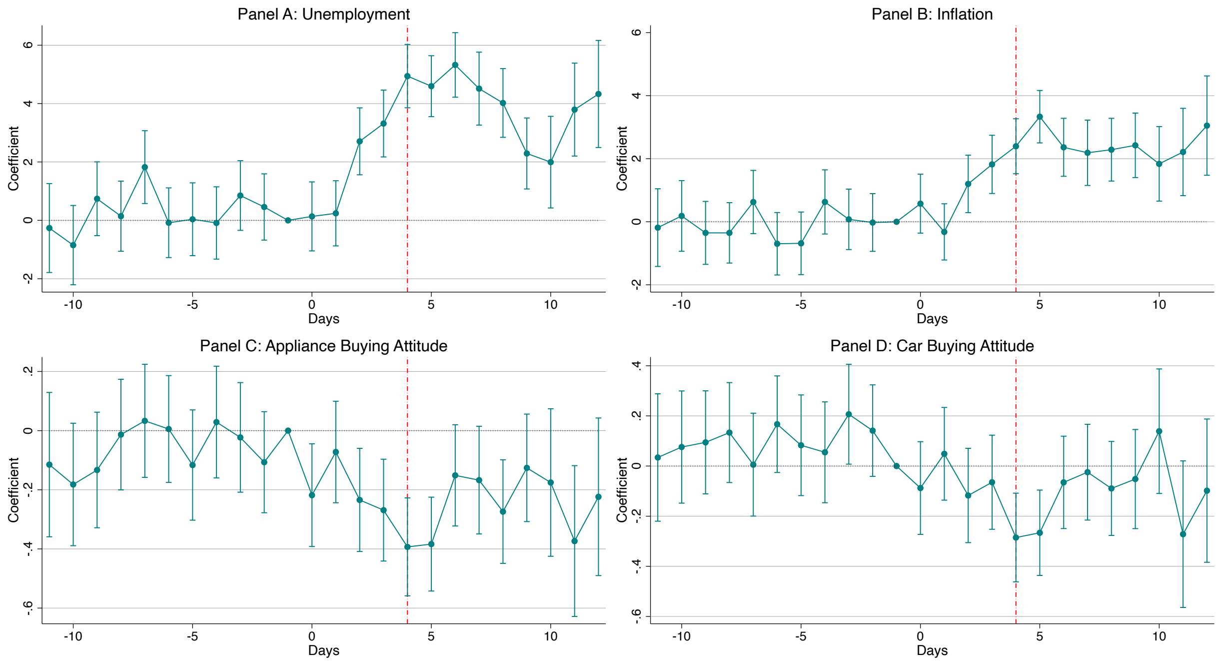


Figure 14: 2020 Event Study of Expectations and Consumption Attitudes

Notes: $\hat{\beta}_\kappa$ from event study described in equation (6) in the days preceding and following the 2020 presidential election. Vertical lines represent 90% confidence intervals. The outcome variables are the respondent's unemployment expectations and inflation expectations in Panels A and B, respectively. The outcome variables in Panels C and D are the respondent's attitudes to purchasing large appliances and cars, where responses range from 1 (very bad time to buy) to 5 (very good time to buy). The vertical line corresponds to the date at which major news agencies called the race for Biden.

in the previous section, and additionally confirms that the response of expectations occur within days following the outcome of the presidential election.

Next, Panels C and D of Figure 14 plot the results regarding attitudes towards consumption decisions. In particular, these questions solicit respondents' attitudes towards buying large appliances (Panel C) or cars (Panel D). For each question, responses range from 1 (very bad time to buy) to 5 (very good time to buy). Although these responses are categorical, we impose a linear specification for these questions in order to simplify the presentation of our results. The results mimic our findings for macroeconomic expectations: in the days following the 2020 election, Republican respondents became more pessimistic about purchasing appliances and cars. Again, the response peaks near the day in which major media organizations called the election for Biden. Hence, whether looking at macroeconomic expectations or consumption attitudes, these results are consistent with our findings from the 2016 election.

In order to assess in more detail how spending reacted to the 2020 election, we link respondents' affiliation with their actual consumption as measured in the Homescan data.

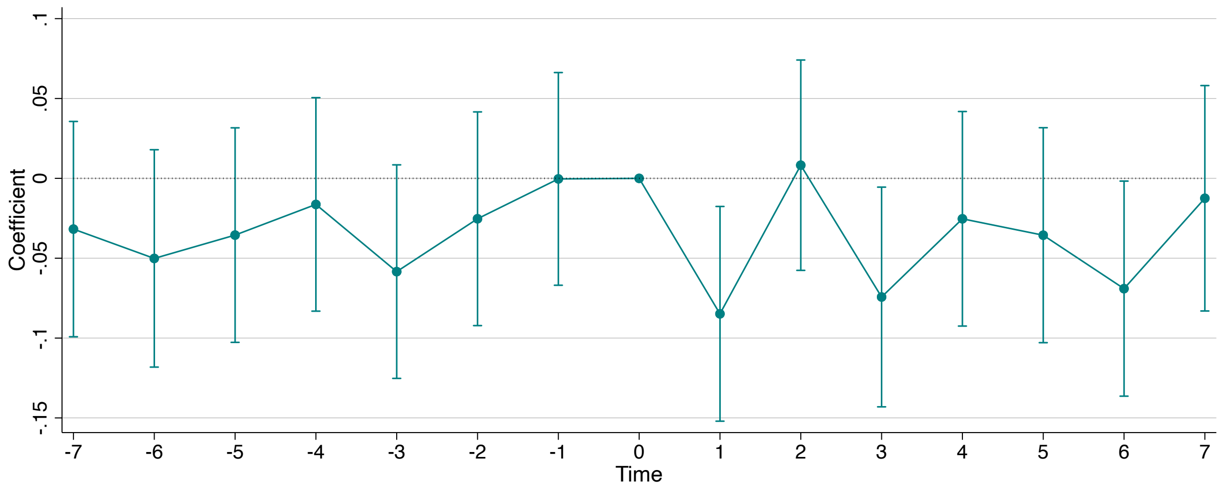


Figure 15: 2020 Event Study of Consumption

Notes: $\hat{\beta}_{\kappa,2020}$ from event study described in equation (7) in the weeks preceding and following the 2020 presidential election. The outcome variable is the respondent's actual weekly (log) consumption as measured by Nielsen Homescan. Vertical lines represent 90% confidence intervals.

We estimate the following event study regression:

$$c_{i,t,y} = \alpha_{i,t} + \gamma_{t,y} + \sum_{k=-\underline{T}}^{\overline{T}} \beta_{k,y} \cdot \mathbf{1}\{i = \text{Republican}\} \cdot \mathbf{1}\{t = k\} + \varepsilon_{i,t,y}. \tag{7}$$

Our specification is the same as in equation (4), with a few differences. First, we observe an individual $i$'s stated political affiliation. Second, we utilize individual-level consumption, $c_{i,t,y}$. Finally, in order to control for potentially different time trends in consumption across Republican and Democratic households, we not only include consumption data from 2020, but also from 2019 (note that we do not include data from years further in the past as the sample of households in the Homescan data changes, as discussed above). Finally, we normalize the event time $t$ such that $t = 0$ corresponds to the week starting at the day in which the 2020 presidential election was called, rather than the day of the election. The coefficient $\beta_{k,2020}$ represents the predicted percent change in consumption for a Republican household relative to a Democratic household before and after the 2020 election.

Figure 15 plots the event study results of realized consumption based on the Nielsen Homescan data from equation (7). In the weeks prior to the election, there is no statistical difference between Democratic and Republican individuals in consumption. However, the point estimates for all weeks in the lead-up to the election are negative, which suggests a degree of possible pre-trends. Following the election of Biden, Republican individuals immediately decrease their consumption relative to Democratic individuals. The effect is

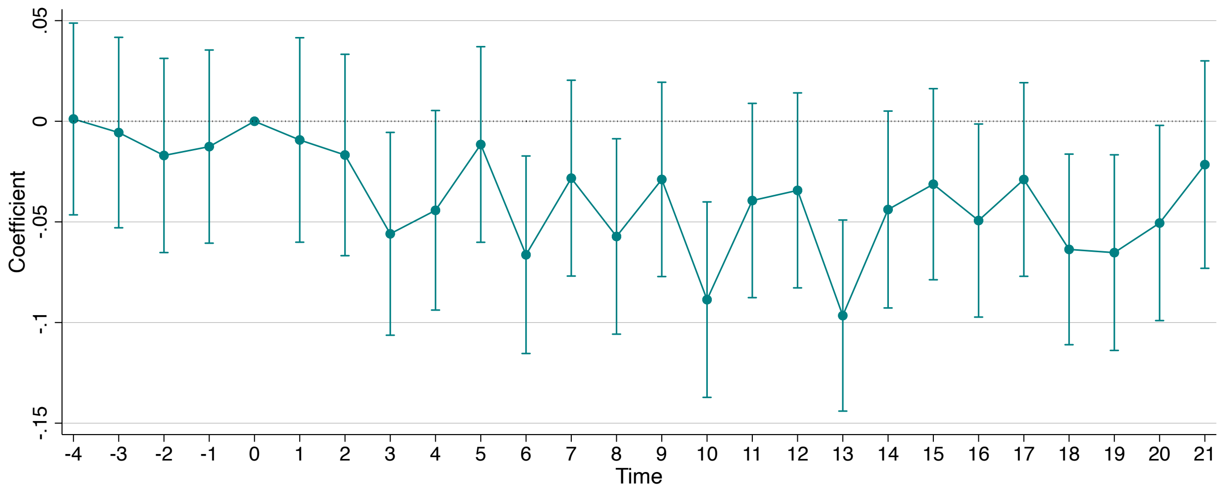


Figure 16: COVID-19 Event Study of Consumption

Notes: $\hat{\beta}_{\kappa,2020}$ from event study described in equation (7) in the bi-weeks preceding and following the outbreak of COVID-19 in the U.S. The outcome variable is the respondent's actual biweekly (log) consumption as measured by Nielsen Homescan. Vertical lines represent 90% confidence intervals.

large, although only at times significant. The differential consumption response is between 5% and 10% in the weeks immediately following the election. Hence, the magnitude of the differential consumption in the 2020 individual-level event study is similar to that of the 2016 zip code-level event study (although our point estimates are somewhat smaller).

Taken as a whole, the results following the 2020 election are in line with what we found following the 2016 election. However, the results are much less stark than 2016. There are many potential reasons for differential consumption reactions to the 2016 and 2020 elections, but one particularly salient difference is that the 2020 election took place within the first year of the COVID-19 outbreak in the U.S. We assess the differential partisan consumption reactions to COVID-19 by estimating equation (7) before and after the COVID-19 outbreak.

Figure 16 reports the results of our COVID-19 event study. In order to study the effects before and after the outbreak across the entire year, we estimate our event study at the bi-weekly frequency (though results are similar at the weekly frequency). We choose mid-March as our event time $t = 0$, as this was when the first wave of lockdowns began in the U.S. We find that Republican households tended to *decrease* consumption following the COVID-19 outbreak, and that this effect persists throughout the entire sample.[17] This decline in consumption is perhaps surprising given the prevailing narrative that Republicans were more lax regarding social-distancing relative to their Democratic counterparts.[18] How-

[17]In Figure 16, the election occurred during bi-week $t = 17$.

[18]For instance, using smartphone tracking data, Gollwitzer et al. (2020) show that Democratic counties practiced more social distancing than Republican counties.

ever, given our measure of consumption, our finding may be due to compositional effects. As discussed above, the Nielsen Homescan dataset primarily covers non-durable and semi-durable purchases made at grocery and big box stores. These goods are largely consumed at home. Hence, the decline in Republican consumption measured in the Nielsen Homescan data may reflect a compositional shift from "at-home" to other types of consumption (relative to Democratic consumers).

**Fact 5: Partisan consumers change their consumption patterns in response to changes in the White House.**

Using a series of event studies around the 2016 presidential election, we find significant and long-lasting increases in Republican relative to Democratic consumption. For the 2020 presidential election, while we find some evidence of an increase in Democratic consumption following Biden's election, the results are noisier and smaller. Although this may represent differences in how partisan consumption reacted to the 2020 election compared to the 2016 election, an important difference is that the 2020 election took place during the COVID-19 outbreak. We find strong evidence of differential partisan consumption reactions to the COVID-19 pandemic.

# 4 Implications for Theory

Our five facts about polarized expectations and consumption have implications for the validity of standard theoretical models of expectation formation. In this section, we discuss these implications by first formalizing our findings in a simple theoretical framework. We then demonstrate that commonly used models of expectation formation struggle to simultaneously explain all of the empirical facts. However, some models can account for some of the existing facts.

In order to formalize our findings we use the following notation: a household denoted by $i$ has subjective beliefs $\mathbb{E}_t^i$. These beliefs may differ from full-information rational expectations, $\mathbb{E}_t$. Let $\mathbf{X}_t$ be a vector of aggregate and individual economic outcomes such as output, inflation, or household consumption at time $t$. The (linearized) dynamics of the economy are summarized by the following equation:

$$\mathbf{X}_{t+1} = \mathbf{A}\mathbf{X}_t + \mathbf{B}\boldsymbol{\varepsilon}_t.$$

The matrix $\mathbf{A}$ governs the transition from period $t$ to $t+1$. The matrix $\mathbf{B}$ specifies the contemporaneous transmission of structural shocks $\boldsymbol{\varepsilon}_t$ (such as the usual set of aggregate supply and demand shocks, as well as "partisan" or political shocks including changes in the

White House). Then the full-information rational expectation of the dynamics of this system is simply $\mathbb{E}_t\mathbf{X}_{t+1} = \mathbf{A}\mathbf{X}_t$. However, household $i$'s perceived dynamics instead are given by:

$$\mathbb{E}_t^i\mathbf{X}_{t+1} = \mathbf{A}^i\mathbb{E}_t^i\mathbf{X}_t + \mathbf{B}^i\mathbb{E}_t^i\boldsymbol{\varepsilon}_t.$$

Hence, household beliefs may differ from FIRE along multiple dimensions: beliefs about dynamics ($\mathbf{A}^i \neq \mathbf{A}, \mathbf{B}^i \neq \mathbf{B}$, where $\mathbf{A}^i, \mathbf{B}^i$ are household $i$'s subjective beliefs about the structural matrices $\mathbf{A}, \mathbf{B}$); beliefs about the distribution of shocks ($\mathbb{E}_t^i\boldsymbol{\varepsilon}_t \neq \mathbf{0}$); or beliefs about the current state of the economy ($\mathbb{E}_t^i\mathbf{X}_t \neq \mathbf{X}_t$). All of these departures will lead to different beliefs about the future state of the economy ($\mathbb{E}_t^i\mathbf{X}_{t+1} \neq \mathbb{E}_t\mathbf{X}_{t+1}$). Many theoretical models of belief formation can be formalized as restrictions on how these objects may differ from FIRE. Using this stylized framework, we discuss each of our five facts in turn.

**Fact 1:** the variance-covariance matrix of household $i$'s beliefs has a rank of approximately one: $\text{rank}(\mathbb{V}\text{ar}^i\,\mathbf{X}_t) \approx 1$. Equivalently, household $i$'s beliefs can be approximated by a single "sentiment" factor $s_t^i$ with an associated vector of loadings: $\mathbb{E}_t^i\mathbf{X}_t \approx \boldsymbol{\lambda}^i \cdot s_t^i$. Additionally, while at any given time there is wide dispersion in beliefs across households, these loadings are similar across a wide range of demographic groups, including political affiliation. Hence, for households $i$ and $j$, we further have $\boldsymbol{\lambda}^i \approx \boldsymbol{\lambda}^j$, and dispersion in beliefs thus must be driven by dispersion in sentiment $s_t^i$.

**Fact 2:** household beliefs exhibit a muted reaction to all innovations, except a presidential election where the White House switches party. Relative to full-information rational expectations, households under-react to nearly all innovations, but over-react to a change in the presidential party. For any outcome variable $x_t \in \mathbf{X}_t$, we have

$$\left|\frac{\partial\mathbb{E}_t^i x_t}{\partial\varepsilon_t}\right| < \left|\frac{\partial\mathbb{E}_t x_t}{\partial\varepsilon_t}\right|, \quad \left|\frac{\partial\mathbb{E}_t^i x_t}{\partial w_t}\right| > \left|\frac{\partial\mathbb{E}_t x_t}{\partial w_t}\right|,$$

where $w_t$ is an innovation to the White House and $\varepsilon_t \in \boldsymbol{\varepsilon}_t$ are all other innovations. Moreover, the switching magnitude in beliefs to changes in the White House has increased over time: $\left|\frac{\partial\mathbb{E}_t^i x_t}{\partial w_t}\right| > \left|\frac{\partial\mathbb{E}_t^i x_\tau}{\partial w_\tau}\right|$ where $t > \tau$.

**Fact 3:** for any two households $i$ and $j$, sentiment $s_t^i$ and $s_t^j$ are correlated across political ideology:

$$\rho(s_t^i, s_t^j) = \begin{cases} > 0 & \text{if } i,\ j \text{ share party affiliation} \\ < 0 & \text{if } i,\ j \text{ do not share party affiliation} \end{cases}$$

Moreover, this correlation has increased in magnitude over time: $\left|\rho(s_t^i, s_t^j)\right| > |\rho(s_\tau^i, s_\tau^j)|$ where $t > \tau$.

**Fact 4:** in order to map our findings to our theoretical framework, we interpret the narrative survey responses as a measure of the subjective importance of a given structural shock. Let $p_t \in \boldsymbol{\varepsilon}_t$ be any "partisan" or political shock (besides innovations to the White House). We have that the subjective importance of partisan shocks has increased over time: $\mathbb{V}\text{ar}^i\, p_t > \mathbb{V}\text{ar}^i\, p_\tau$ where $t > \tau$. These shocks also affect household beliefs, but outside of innovations to the White House, the transmission of these partisan shocks to beliefs has remained constant: $\frac{\partial \mathbb{E}_t^i x_t}{\partial p_t} \approx \frac{\partial \mathbb{E}_t^i x_\tau}{\partial p_\tau} \neq 0$.

**Fact 5:** the consumption decisions $c_t^i$ for household $i$ respond to changes in the White House: $\frac{\partial c_t^i}{\partial w_t} \neq 0$. Moreover, $\frac{\partial c_t^i}{\partial w_t} > 0$ if and only if household $i$ shares the political affiliation of the party taking control of the White House.

With this formalization, we discuss implications of our facts for many leading theories of expectation formation.

**Full-Information Rational Expectations:** The workhorse approach to modelling expectations in macroeconomics has been FIRE since the rational expectations revolution of the 1970s (e.g., Muth 1961, Lucas Jr 1972, Lucas 1976, and Lucas and Sargent 1979). However, ensuing work using survey-based measures of expectations has consistently documented deviations from FIRE such as forecast error predictability and persistent biases (see Coibion et al. 2018 for a summary of the literature).

Unsurprisingly, our five empirical facts also clearly contradict the assumption that household beliefs are full-information and rational. The key failures of FIRE with respect to our facts are two-fold. First, rational agents fully understand the dynamics of the model, and so the only difference between forecasts and outcomes are due to unpredictable shocks. However, Fact 1 implies that consumer beliefs have a lower dimension than the actual data-generating process.[19] Second, models with full-information rational expectations typically imply that beliefs are the same across all agents. Even if this assumption is slightly relaxed, belief dispersion is not predictable under FIRE. Fact 3 shows that dispersion in expectations is large, and moreover this dispersion is predictable by political affiliation.

**Models of Under/Over-Reaction:** There is a large class of models that depart from FIRE and imply that agents will either under-react or over-react to shocks relative to FIRE. For example, under-reaction of beliefs due to incomplete information is a feature of models such as rational inattention (Sims 2003), sticky information (Mankiw and Reis 2007), adaptive

[19] Our analysis in Section 2.2 also showed that consumer beliefs exhibit lower dimensionality than professional beliefs, which may be closer to FIRE.

learning (Evans and Honkapohja 2012), and sparsity (Gabaix 2014). On the other hand, diagnostic expectations may suggest an over-reaction to incoming news (Bordalo et al. 2018).

Our findings strongly suggest that household beliefs over-react to changes in the White House, but under-react to other news.[20] Hence, theories which attempt to rationalize this behavior clearly must feature different types of under- and over-reaction. However, standard formulations of the models discussed above typically result in agents reacting the same way to all shocks. That is, agents either always under-react $\left(\left|\frac{\partial \mathbb{E}_t^i x_t}{\partial \varepsilon_t}\right| < \left|\frac{\partial \mathbb{E}_t x_t}{\partial \varepsilon_t}\right|\right)$ or always over-react $\left(\left|\frac{\partial \mathbb{E}_t^i x_t}{\partial \varepsilon_t}\right| > \left|\frac{\partial \mathbb{E}_t x_t}{\partial \varepsilon_t}\right|\right)$. This is inconsistent with Fact 2: households under-react to many shocks, while simultaneously over-reacting to changes in the White House.

**Robustness/Ambiguity Models:** Robustness-based models (e.g., Hansen and Sargent 2001b, Hansen and Sargent 2001a, and Bhandari et al. 2022) imply that agents act as if the worst states of the world are more likely to occur than in reality, and this may be reflected in survey responses.[21] Then a robustness-based explanation could explain the large reaction to changes in the White House if agents believe the worst possible states of the world have changed following the election. However, these models would imply that agents would react to the outcome of presidential elections where the party did not change. For example, suppose an individual prefers the party currently in power. The "worst-case" outcomes for this agent are more likely to occur if the challenging party were to win. Hence, following the realization of the election wherein the current party retains power, the worst-case states of the world have improved and the agent would become more optimistic. In contrast, we find that empirically beliefs are stable around elections where the party in the White House remains unchanged. Moreover, to the extent worst-case outcomes are related to economic policy, these models would also imply reactions to non-presidential elections (such as midterm Congressional elections). Hence, models of robustness with respect to political outcomes are not fully consistent with Fact 2.

**Agree-to-Disagree Models**: Clearly, our results show that there is a huge range of disagreement across individuals. Moreover, it is common knowledge that the Democratic and Republican parties disagree strongly across a wide range of issues. However, our results are not necessarily consistent with the "agree-to-disagree" models in the literature. These models feature agents who "disagree" about the model of the world or the parameters that govern it, but these agents also "agree" to not learn from others' behavior (e.g., Dumas et al.

[20] Again, we can use our results from the SPF as a point of comparison: professional forecasters do not react nearly as strongly to presidential elections as do households; but these agents do react more strongly to other macroeconomic fluctuations.

[21] Note that formally, robust agents recognize this, so it is unclear what a robust agent is reporting when answering surveys. In principle, a robust agent with full information would still report their true expectations, not their worst-outcome-skewed beliefs.

2009 and David 2008).

However, typically "full-information" agree-to-disagree models imply that while agents disagree about future outcomes, they do not disagree about the current state of the economy: $\mathbb{E}_t^i\mathbf{X}_t = \mathbb{E}_t^j\mathbf{X}_t = \mathbf{X}_t$. Moreover, these models feature agents who have different underlying (potentially misspecified) models of the world. In our stylized framework, we would therefore expect that the factor loadings would also differ across agents: $\boldsymbol{\lambda}^i \neq \boldsymbol{\lambda}^j$. Hence, these models are inconsistent with Facts 1 and 2.

Finally, in the context of elections and political affiliation, an "agree-to-disagree" model would likely feature disagreement about government policy, not about the presidency *per se*. While control of the White House is of course important for shaping government policy, other aspects (such as Congressional control) also play a large role. This would imply that beliefs should respond to Congressional midterm elections in a similar way to presidential elections: $\frac{\partial \mathbb{E}_t^i x_t}{\partial m_t} \approx \frac{\partial \mathbb{E}_t^i x_t}{\partial w_t}$ where $m_t$ are innovations to Congress. Hence, agree-to-disagree models of this type would exhibit further inconsistencies with Fact 2.

**Cheerleading Models:** In models of "cheerleading", agents do not report their true beliefs, but instead report optimistic beliefs when their preferred party is in power and vice versa (e.g., Bullock et al. 2015, Prior et al. 2015, and Peterson and Iyengar 2021). Our results certainly do not rule out some degree of "cheerleading" in survey responses. However, a pure cheerleading model is inconsistent with actual changes in consumption (Fact 5). Note that while we can rule out pure cheerleading models, we are silent on whether consumption responds by as much as it would if surveys fully reflected true beliefs.

Two competing explanations for our findings (beyond the scope of standard economic expectation formation models) deserve some consideration as well. The first hypothesis is that over time, households have become more likely to hold the subjective view that only the presidency matters for economic outcomes. The second is that over time, households believe that the importance of government (broadly defined) for economic outcomes is growing. However, Fact 4 is not fully consistent with either of these simple explanations. Our results show that households do not ignore other non-presidential partisan or political shocks, and indeed the subjective importance of these events is increasing as well. However, the reaction of household beliefs to these shocks has been stable over time. Our results show that it is only changes in the White House which are increasingly important and singular events for driving household expectations.

# 5 Concluding Remarks

This paper argues that political polarization plays a large and growing role in how individuals both form economic beliefs and make economic decisions. First, we show that household beliefs are well-described by a single factor, with nearly identical factor structures regardless of political affiliation (or other demographic indicators). Second, within households beliefs are typically persistent, but change dramatically when there is a change in the White House. Third, there is massive heterogeneity in beliefs across households at any given point in time, and political affiliation is an increasingly strong predictor of this dispersion. Fourth, households are increasingly likely to report partisan reasons as justifications for their economic beliefs; however, outside of elections the effect of changing partisan narratives on economic beliefs is stable over time. Fifth, consumption responds differentially along party lines following changes in the White House.

Standard theoretical models of expectation formation struggle to simultaneously explain all five of our empirical facts. We show that commonly-used models such as FIRE, models of consistent under- or overreaction to news, models of robustness, agree-to-disagree models, and cheerleading models can only explain some of the facts. Thus, we hope that our findings will help guide the development of new theoretical models of household expectation formation.

# References


Alesina, A., Stantcheva, S., and Teso, E. (2018). Intergenerational Mobility and Preferences for Redistribution. *American Economic Review*, 108(2):521–54.

Alesina, A. F., Miano, A., and Stantcheva, S. (2020). The Polarization of Reality. NBER Working Papers 26675, National Bureau of Economic Research, Inc.

Allcott, H., Boxell, L., Conway, J., Gentzkow, M., Thaler, M., and Yang, D. (2020). Polarization and Public Health: Partisan Differences in Social Distancing During the Coronavirus Pandemic. *Journal of Public Economics*, 191(C).

Andre, P., Haaland, I., Roth, C., Wohlfart, J., and Haaland, I. K. (2023). Narratives About the Macroeconomy. CESifo Working Paper Series 10535, CESifo.

Andre, P., Pizzinelli, C., Roth, C., and Wohlfart, J. (2022). Subjective Models of the Macroeconomy: Evidence from Experts and Representative Samples. *The Review of Economic Studies*, 89(6):2958–2991.

Armantier, O., Bruine de Bruin, W., Topa, G., van der Klaauw, W., and Zafar, B. (2015). Inflation Expectations and Behavior: Do Survey Respondents Act on Their Beliefs. *International Economic Review*, 56(2):505–536.

Bachmann, R., Berg, T. O., and Sims, E. R. (2015). Inflation Expectations and Readiness to Spend: Cross-Sectional Evidence. *American Economic Journal: Economic Policy*, 7(1):1–35.

Bachmann, R., Topa, G., and van der Klaauw, W. (2022). *Handbook of Economic Expectations*. Elsevier.

Bartels, L. M. (2002). Beyond the Running Tally: Partisan Bias in Political Perceptions. *Political Behavior*, 24(2):117–150.

Bénabou, R., Falk, A., and Tirole, J. (2018). Narratives, Imperatives, and Moral Reasoning. NBER Working Papers 24798.

Benhabib, J. and Spiegel, M. M. (2019). Sentiments and Economic Activity: Evidence from US States. *Economic Journal*, 129(618):715–733.

Bertrand, M. and Kamenica, E. (2018). Coming Apart? Cultural Distances in the United States Over Time. NBER Working Papers 24771.

Bhandari, A., Borovička, J., and Ho, P. (2022). Survey Data and Subjective Beliefs in Business Cycle Models. *Available at SSRN 2763942*.

Bonaparte, Y., Kumar, A., and Page, J. K. (2017). Political Climate, Optimism, and Investment Decisions. *Journal of Financial Markets*, 34:69–94.

Bordalo, P., Gennaioli, N., and Shleifer, A. (2018). Diagnostic Expectations and Credit Cycles. *The Journal of Finance*, 73(1):199–227.

Bruine de Bruin, W., van der Klaauw, W., Downs, J. S., Fischhoff, B., Topa, G., and Armantier, O. (2010). Expectations of Inflation: The Role of Demographic Variables, Expectation Formation, and Financial Literacy. *The Journal of Consumer Affairs*, 44(2):381–402.

Bryan, M. F. and Venkatu, G. (2001). The Curiously Different Inflation Perspectives of Men and Women. *Economic Commentary*, (Nov).

Bullock, J. G., Gerber, A. S., Hill, S. J., and Huber, G. A. (2015). Partisan Bias in Factual Beliefs about Politics. *Quarterly Journal of Political Science*, 10(4):519–578.

Bursztyn, L., Rao, A., Roth, C., and Yanagizawa-Drott, D. (2023). Opinions as Facts. *Review of Economic Studies*, 90(4):1832–1864.

Carstensen, K. and Bachmann, R. (2023). Firm Surveys. *Handbook of Economic Expectations*, pages 33–70.

Carvalho, C. and Nechio, F. (2014). Do People Understand Monetary Policy? *Journal of Monetary Economics*, 66(C):108–123.

Cassidy, W. and Vorsatz, B. (2021). Partisanship and Portfolio Choice: Evidence from Mutual Funds. Manuscript.

Coibion, O., Georgarakos, D., Gorodnichenko, Y., and van Rooij, M. (2019a). How Does Consumption Respond to News about Inflation? Field Evidence from a Randomized Control Trial. NBER Working Paper 26106.

Coibion, O., Gorodnichenko, Y., and Kamdar, R. (2018). The Formation of Expectations, Inflation, and the Phillips Curve. *Journal of Economic Literature*, 56(4):1447–1491.

Coibion, O., Gorodnichenko, Y., and Ropele, T. (2019b). Inflation Expectations and Firm Decisions: New Causal Evidence. *The Quarterly Journal of Economics*, 135(1):165–219.

Coibion, O., Gorodnichenko, Y., and Weber, M. (2020). Political Polarization and Expected Economic Outcomes. Manuscript.

D'Acunto, F., Hoang, D., and Weber, M. (2022). Managing Households Expectations with Unconventional Policies. *Review of Financial Studies*, 35(4):1597–1642.

D'Acunto, F., Malmendier, U., and Weber, M. (2023). What Do the Data Tell Us About Inflation Expectations? In *Handbook of Economic Expectations*, pages 133–161. Elsevier.

Dagostino, R., Gao, J., and Ma, P. (2020). Partisanship in Loan Pricing. Manuscript.

David, A. (2008). Heterogeneous Beliefs, Speculation, and the Equity Premium. *The Journal of Finance*, 63(1):41–83.

DellaVigna, S. and Kaplan, E. (2007). The Fox News Effect: Media Bias and Voting. *The Quarterly Journal of Economics*, 122(3):1187–1234.

Dräger, L., Lamla, M. J., and Pfajfar, D. (2016). Are Survey Expectations Theory-Consistent? The Role of Central Bank Communication and News. *European Economic Review*, 85(C):84–111.

Dumas, B., Kurshev, A., and Uppal, R. (2009). Equilibrium Portfolio Strategies in the Presence of Sentiment Risk and Excess Volatility. *The Journal of Finance*, 64(2):579–629.

Evans, G. W. and Honkapohja, S. (2012). Learning and Expectations in Macroeconomics. In *Learning and Expectations in Macroeconomics*. Princeton University Press.

Gabaix, X. (2014). A Sparsity-Based Model of Bounded Rationality. *The Quarterly Journal of Economics*, 129(4):1661–1710.

Galashin, M., Kanz, M., and Perez-Truglia, R. (2020). Macroeconomic Expectations and Credit Card Spending. NBER Working Papers 28281.

Gentzkow, M. and Shapiro, J. M. (2010). What Drives Media Slant? Evidence from U.S. Daily Newspapers. *Econometrica*, 78(1):35–71.

Gerber, A. S. and Huber, G. A. (2009). Partisanship and Economic Behavior: Do Partisan Differences in Economic Forecasts Predict Real Economic Behavior? *American Political Science Review*, 103(3):407–426.

Gillitzer, C. and Prasad, N. (2018). The Effect of Consumer Sentiment on Consumption: Cross-Sectional Evidence from Elections. *American Economic Journal: Macroeconomics*, 10(4):234–269.

Gillitzer, C., Prasad, N., and Robinson, T. (2021). Political Attitudes and Inflation Expectations: Evidence and Implications. *Journal of Money, Credit and Banking*, 53(4):605–634.

Gollwitzer, A., Martel, C., Brady, W. J., Pärnamets, P., Freedman, I. G., Knowles, E. D., and Van Bavel, J. J. (2020). Partisan Differences in Physical Distancing Are Linked to Health Outcomes During the COVID-19 Pandemic. *Nature Human Behaviour*, 4(11):1186–1197.

Hansen, L. P. and Sargent, T. J. (2001a). Acknowledging Misspecification in Macroeconomic Theory. *Review of Economic Dynamics*, 4(3):519–535.

Hansen, L. P. and Sargent, T. J. (2001b). Robust Control and Model Uncertainty. *American Economic Review*, 91(2):60–66.

Jerit, J. and Barabas, J. (2012). Partisan Perceptual Bias and the Information Environment. *The Journal of Politics*, 74(3):672–684.

Kamdar, R. (2019). The Inattentive Consumer: Sentiment and Expectations. Manuscript.

Kempf, E. and Tsoutsoura, M. (2021). Partisan Professionals: Evidence From Credit Rating Analysts. *The Journal of Finance*, 76(6):2805–2856.

Kőszegi, B. and Matějka, F. (2020). Choice Simplification: A Theory of Mental Budgeting and Naive Diversification. *The Quarterly Journal of Economics*, 135(2):1153–1207.

Kuchler, T., Piazzesi, M., and Stroebel, J. (2023). Housing Market Expectations. In *Handbook of Economic Expectations*, pages 163–191. Elsevier.

Ladner, M. and Wlezien, C. (2007). Partisan Preferences, Electoral Prospects, and Economic Expectations. *Comparative Political Studies*, 40(5):571–596.

Larcinese, V., Puglisi, R., and Snyder, J. M. (2011). Partisan Bias in Economic News: Evidence on the Agenda-Setting Behavior of U.S. Newspapers. *Journal of Public Economics*, 95(9):1178–1189. Special Issue: The Role of Firms in Tax Systems.

Levy, G. and Razin, R. (2019). Echo Chambers and Their Effects on Economic and Political Outcomes. *Annual Review of Economics*, 11(1):303–328.

Levy, R. (2021). Social Media, News Consumption, and Polarization: Evidence from a Field Experiment. *American Economic Review*, 111(3):831–870.

Lucas, R. E. and Sargent, T. (1979). After Keynesian Macroeconomics. *Federal Reserve Bank of Minneapolis Quarterly Review*, 3(2):1–16.

Lucas, R. J. (1976). Econometric Policy Evaluation: A Critique. *Carnegie-Rochester Conference Series on Public Policy*, 1(1):19–46.

Lucas Jr, R. E. (1972). Expectations and the Neutrality of Money. *Journal of economic theory*, 4(2):103–124.

Malmendier, U. and Nagel, S. (2016). Learning from Inflation Experiences. *The Quarterly Journal of Economics*, 131(1):53–87.

Mankiw, N. G. and Reis, R. (2007). Sticky Information in General Equilibrium. *Journal of the European Economic Association*, 5(2-3):603–613.

Martin, G. J. and Yurukoglu, A. (2017). Bias in Cable News: Persuasion and Polarization. *American Economic Review*, 107(9):2565–99.

Meeuwis, M., Parker, J. A., Schoar, A., and Simester, D. I. (2022). Belief Disagreement and Portfolio Choice. *The Journal of Finance*, 77(6):3191–3247.

Mian, A., Sufi, A., and Khoshkhou, N. (2021). Partisan Bias, Economic Expectations, and Household Spending. *The Review of Economics and Statistics*, pages 1–46.

Mullainathan, S. and Shleifer, A. (2005). The Market for News. *American Economic Review*, 95(4):1031–1053.

Muth, J. F. (1961). Rational Expectations and the Theory of Price Movements. *Econometrica: Journal of the Econometric Society*, pages 315–335.

Peterson, E. and Iyengar, S. (2021). Partisan Gaps in Political Information and Information-Seeking Behavior: Motivated Reasoning or Cheerleading? *American Journal of Political Science*, 65(1):133–147.

Pew Research Center (2014). Political Polarization in the American Public. Technical report.

Prior, M., Sood, G., Khanna, K., et al. (2015). You Cannot be Serious: The Impact of Accuracy Incentives on Partisan Bias in Reports of Economic Perceptions. *Quarterly Journal of Political Science*, 10(4):489–518.

Rice, A. (2020). Executive Partisanship and Corporate Investment. Manuscript.

Roth, C. and Wohlfart, J. (2020). How Do Expectations about the Macroeconomy Affect Personal Expectations and Behavior? *The Review of Economics and Statistics*, 102(4):731–748.

Shiller, R. J. (2017). Narrative Economics. *American Economic Review*, 107(4):967–1004.

Shiller, R. J. (2020). *Narrative Economics: How Stories Go Viral and Drive Major Economic Events*. Princeton University Press.

Sims, C. A. (2003). Implications of Rational Inattention. *Journal of Monetary Economics*, 50(3):665–690.

Sims, C. A. (2010). Rational Inattention and Monetary Economics. In Friedman, B. M. and Woodford, M., editors, *Handbook of Monetary Economics*, volume 3 of *Handbook of Monetary Economics*, chapter 4, pages 155–181. Elsevier.

Stuart, M. D., Wang, J., and Willis, R. H. (2021). CEO Partisan Bias and Management Earnings Forecast Bias. Manuscript.

# Appendix A Additional Tables and Figures

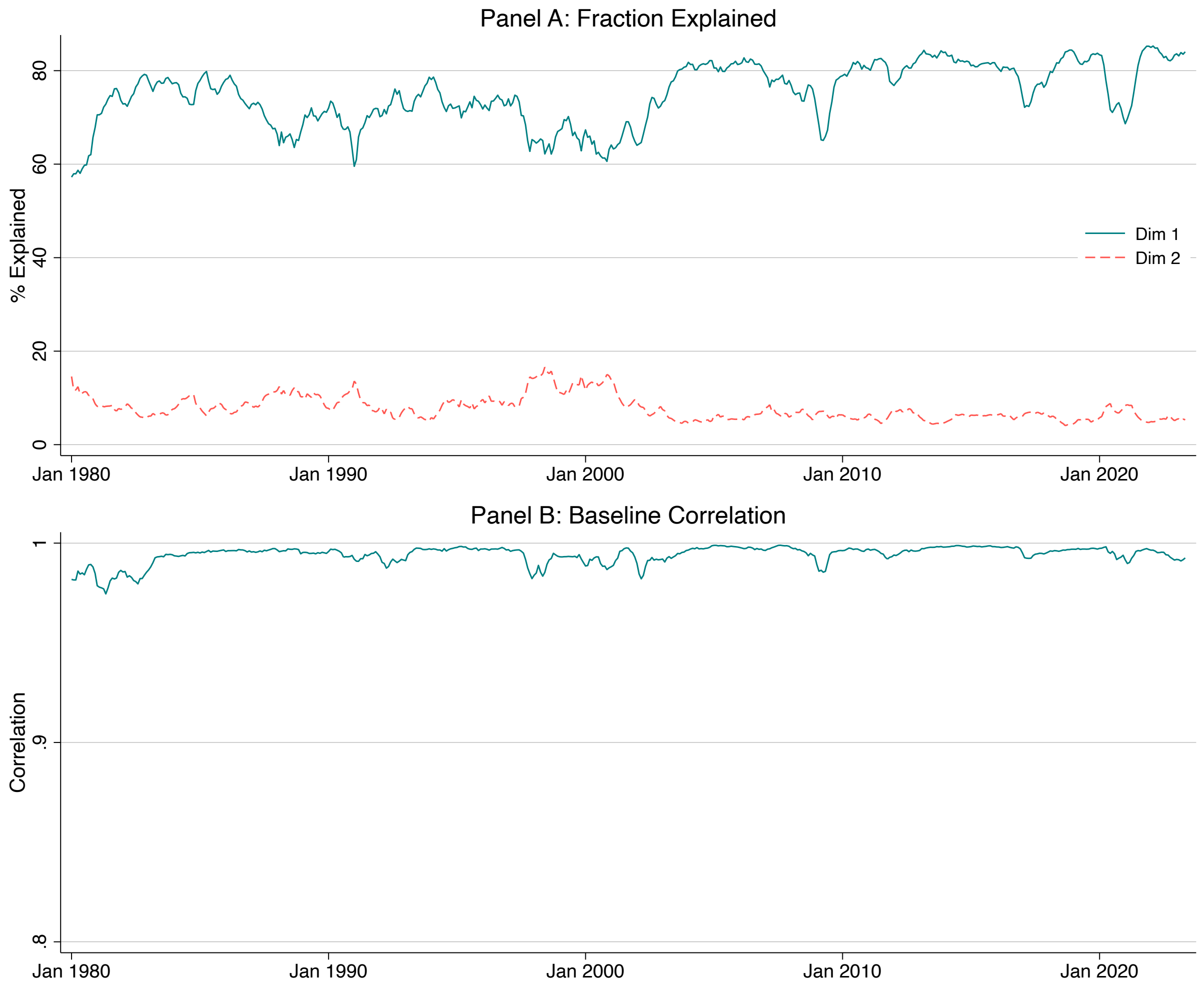


Figure A1: Rolling MCA

Notes: Panel A plots the fraction explained by the first and second component of the baseline MCA performed on rolling six-month samples. Panel B plots the correlation of the fitted first component over the rolling six-month window and the baseline sentiment (fitted first component of an MCA over the whole sample).

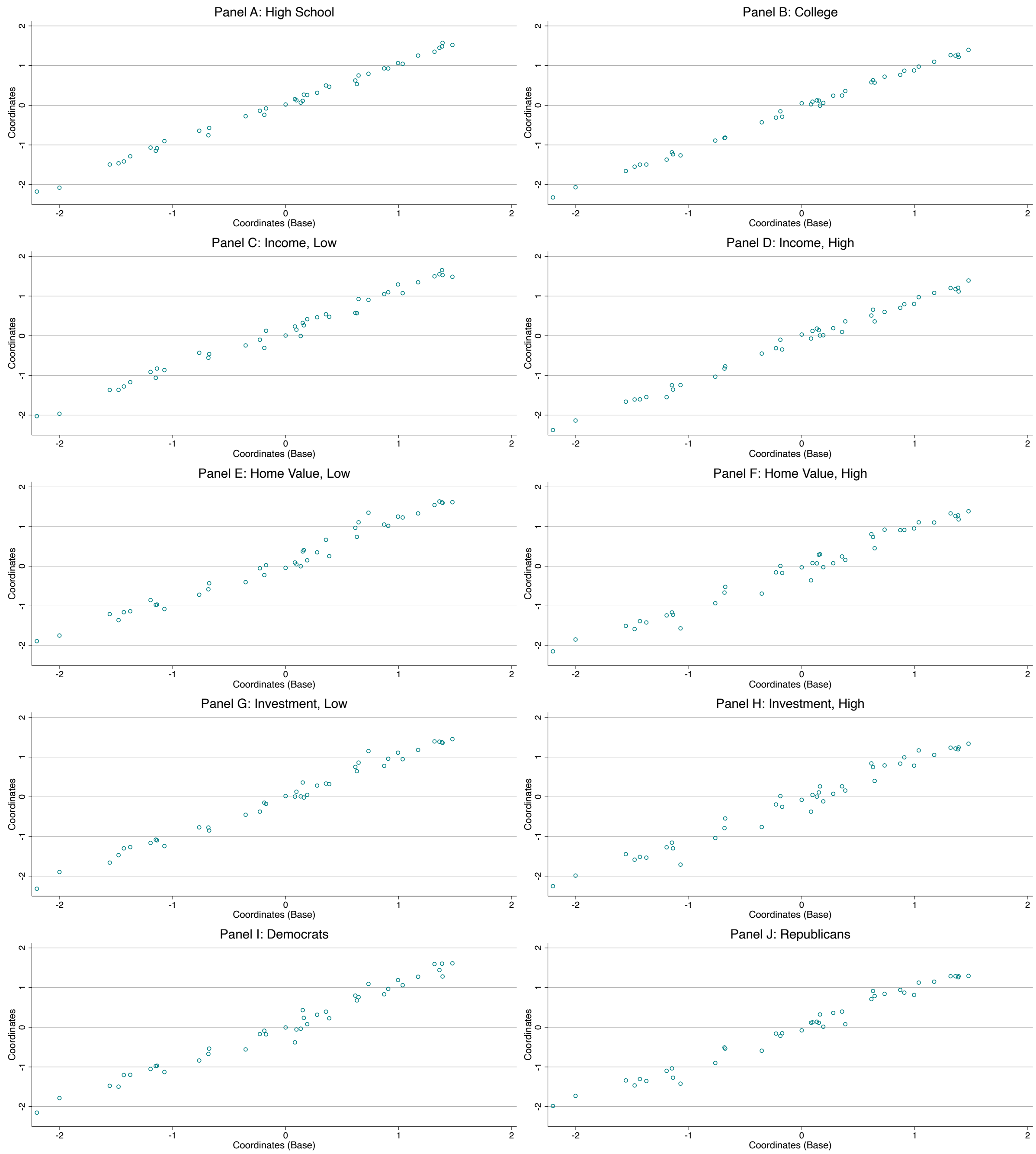


Figure A2: MCA by Demographic Groups, Loadings

Notes: each panel plots the estimated loadings in the baseline MCA on the horizontal axis and the estimated loadings in the baseline MCA conducted on a subgroup of individuals.

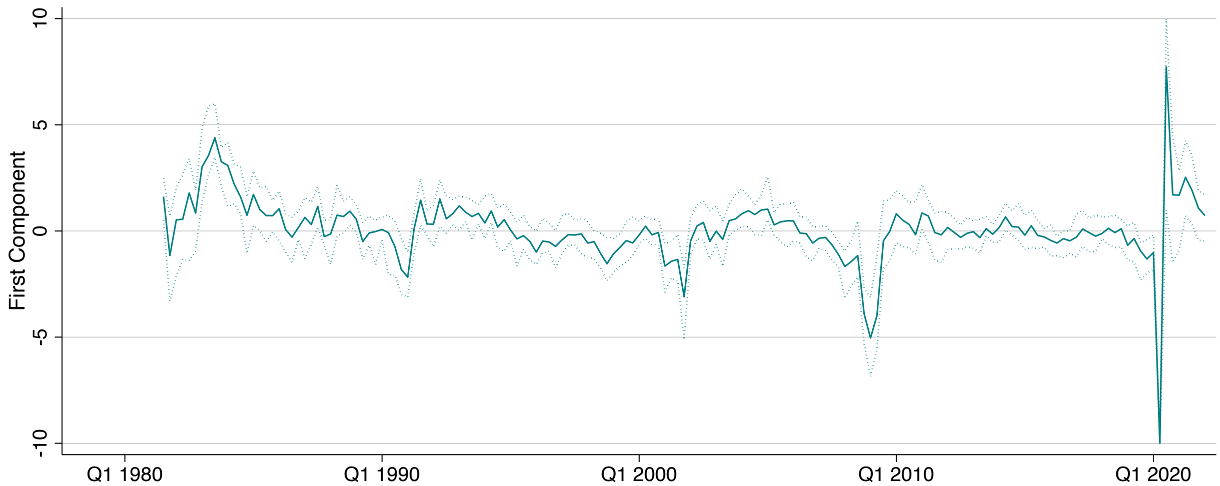


Figure A3: Professionals PCA First Component Distribution Across Time

Notes: time series of the first component of the PCA of the Survey of Professional Forecasters. See Table A1 for the questions included in the PCA. The solid line is the median value, while the dotted lines are 90-10 percentiles.


Figure A4: Rolling PCA, Professionals

Notes: Panel A plots the fraction explained by the first and second component of the PCA performed on rolling two-quarter samples. Panel B plots the correlation of the fitted first component over the rolling two-quarter window and the baseline first component of the PCA (described in Table A1 and estimated over the whole sample).

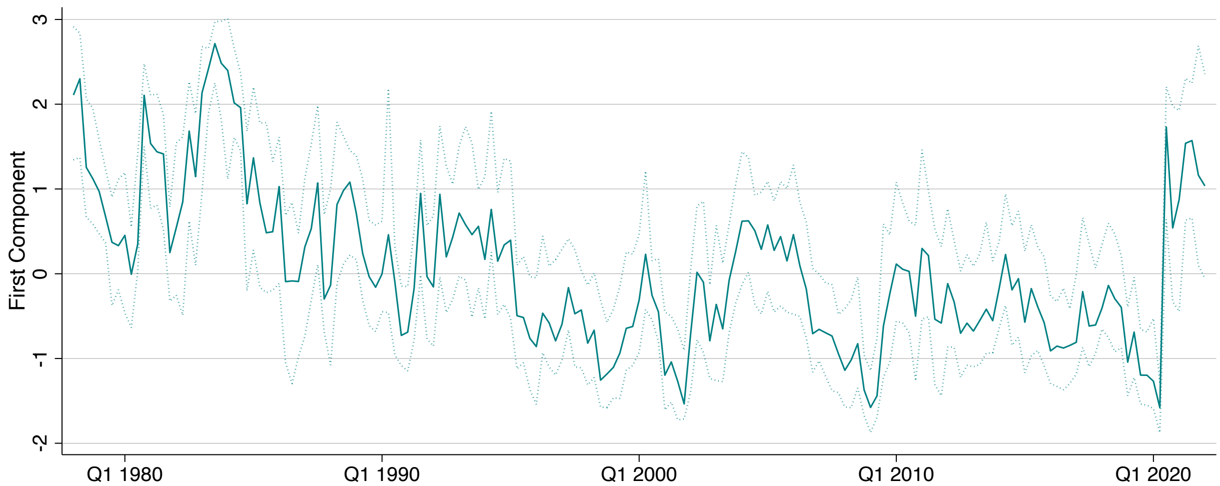


Figure A5: Professionals Psuedo-MCA First Component Distribution Across Time

Notes: time series of the first component from a “pseudo-MCA” of the Survey of Professional Forecasters. See Table A1 for the questions included in the MCA. Responses are binned into quintiles. The solid line is the median value, while the dotted lines are 90-10 percentiles.

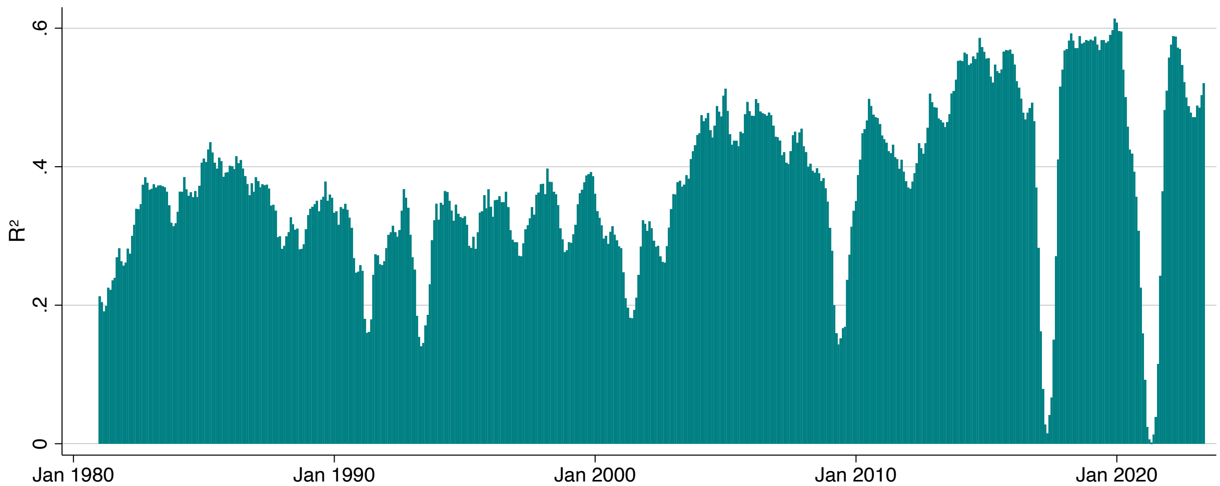


Figure A6: R-squared of Persistence Regressions

Notes: $R^2$ from the rolling regressions in Figure 3 Panel A.

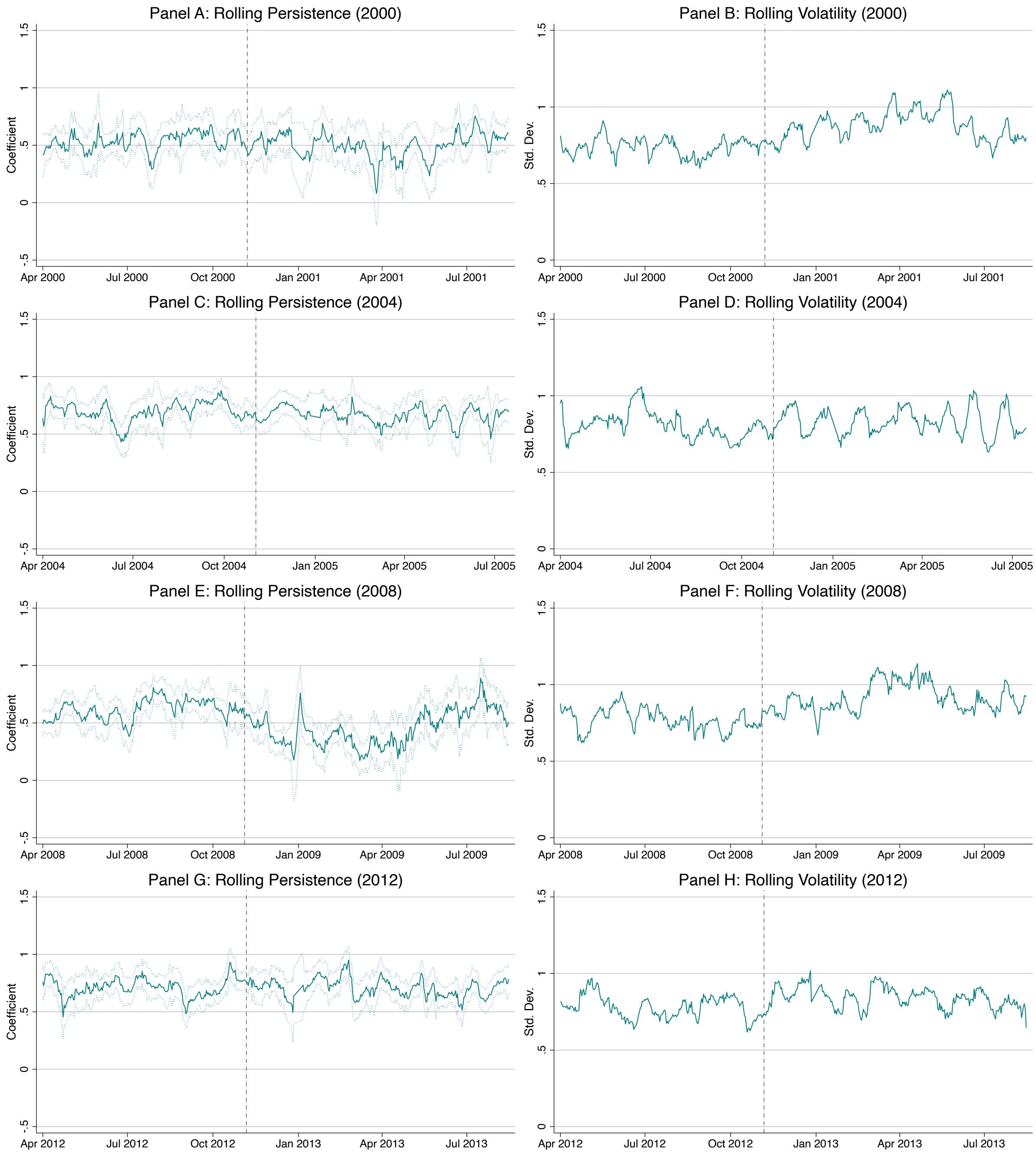


Figure A7: Daily Persistence and Volatility of Sentiment, Additional Elections

Notes: analogous to Figure 4 for presidential elections from 2000 through 2012.

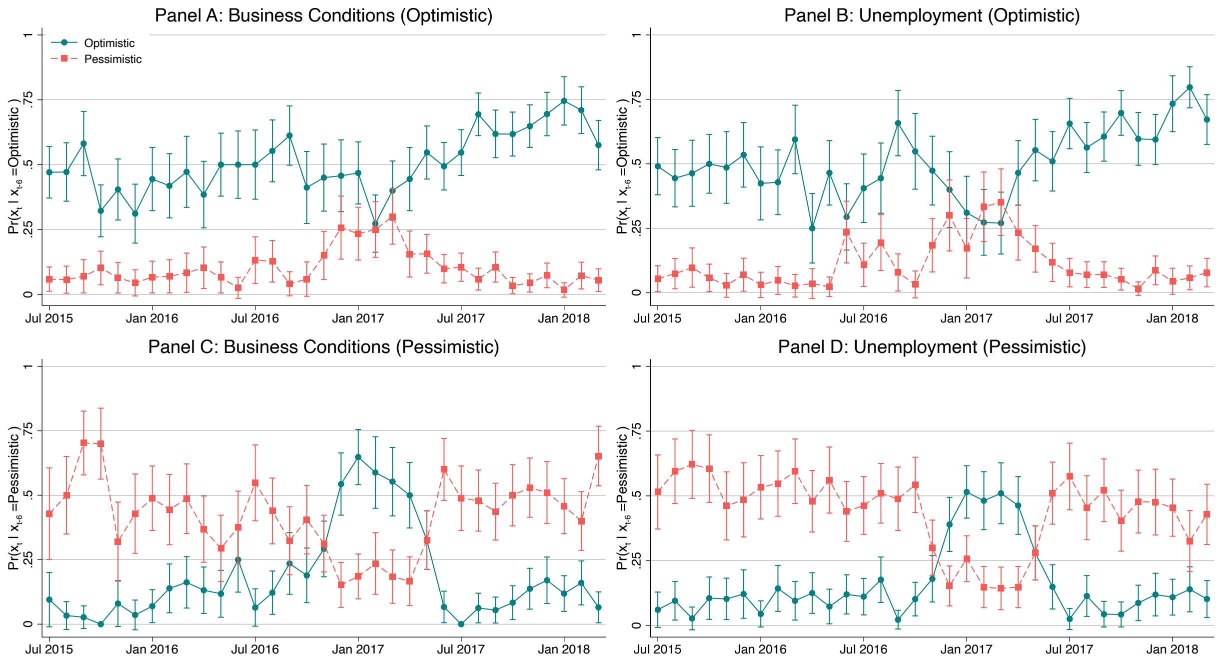


Figure A8: Switching Probabilities, 2016-2018

Notes: probability of an optimistic or pessimistic response conditional on an individual giving an optimistic response (Panels A and B) or pessimistic response (Panels C and D) in the previous survey six months ago. Survey questions are from the MSC regarding business conditions (Panels A and C) or unemployment (Panels B and D). Teal circles represent the conditional probability of an optimistic response. Orange squares represent the conditional probability of a pessimistic response. Estimates from a period-by-period multinomial logit model; vertical lines represent 90% confidence intervals.

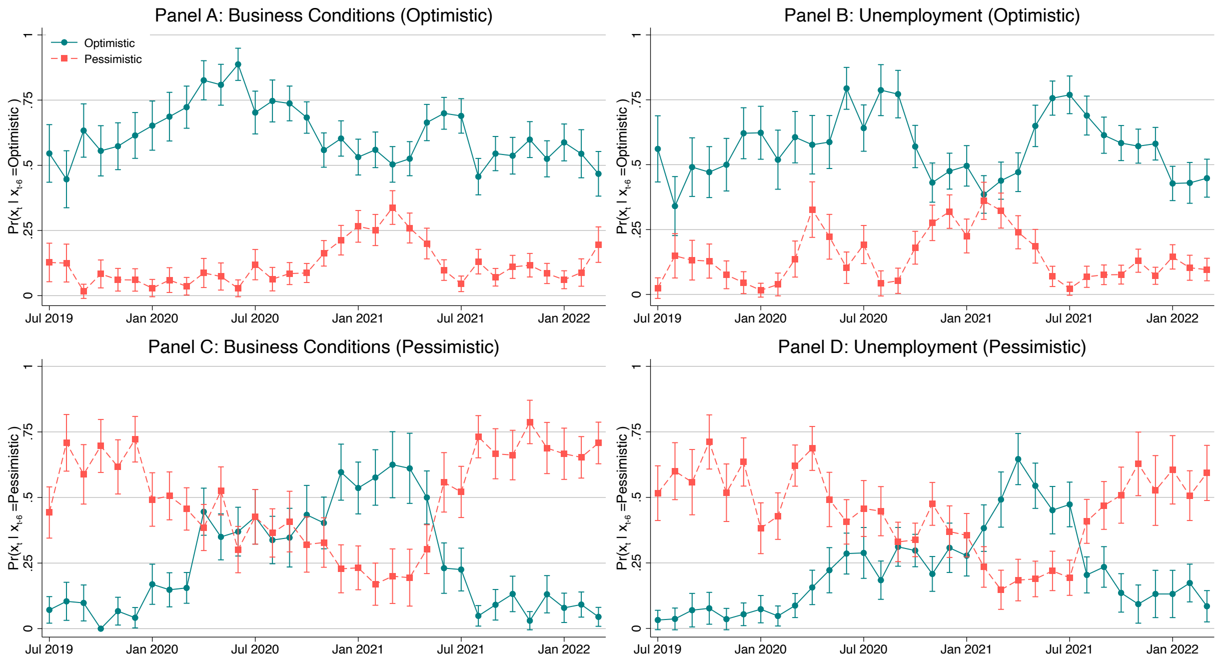


Figure A9: Switching Probabilities, 2020-2022

Notes: probability of an optimistic or pessimistic response conditional on an individual giving an optimistic response (Panels A and B) or pessimistic response (Panels C and D) in the previous survey six months ago. Survey questions are from the MSC regarding business conditions (Panels A and C) or unemployment (Panels B and D). Teal circles represent the conditional probability of an optimistic response. Orange squares represent the conditional probability of a pessimistic response. Estimates from a period-by-period multinomial logit model; vertical lines represent 90% confidence intervals.

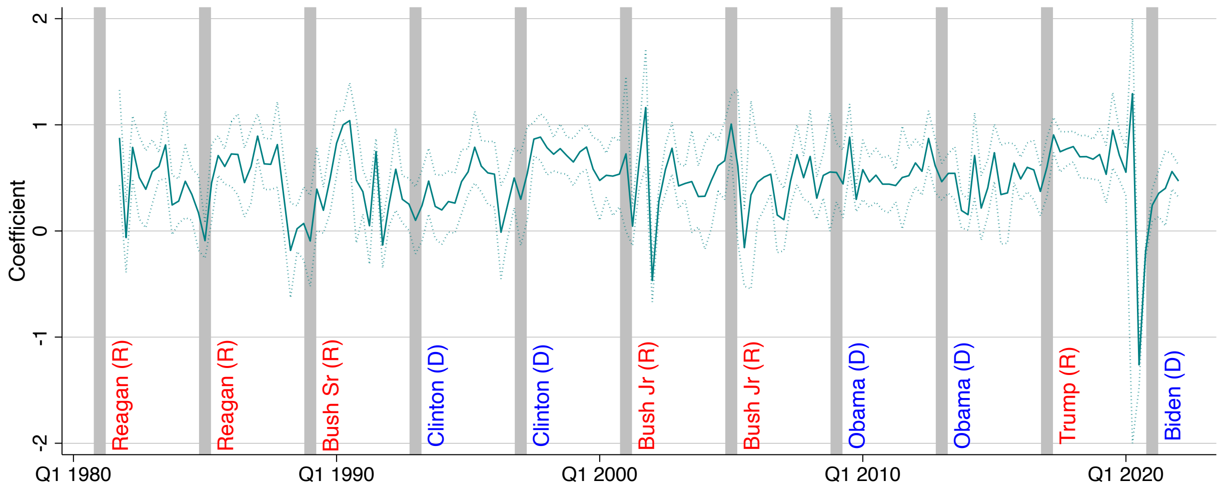


Figure A10: Persistence of the First Component, Professionals PCA

Notes: rolling coefficients of the fitted first component (from the PCA described in Table A1) regressed on the fitted first component of the previous quarter. We use two-quarter rolling windows and pool across respondents. Shaded regions correspond to the three quarters following presidential elections. Dotted lines represent 90% confidence intervals.

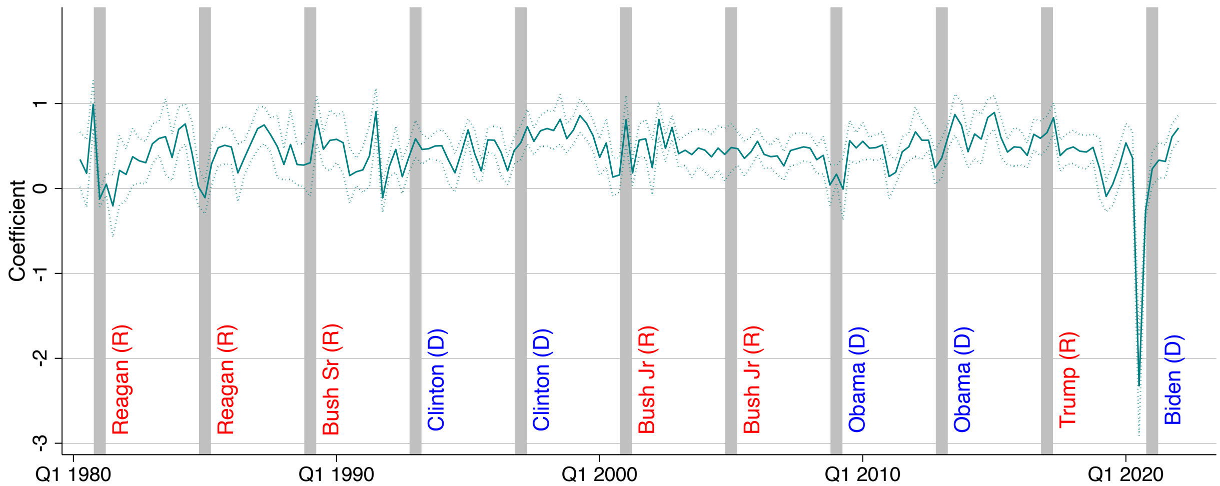


Figure A11: Persistence of of the First Component, Professionals Pseudo-MCA

Notes: rolling coefficients of the fitted first component (from the pseudo-MCA described in Figure A5) regressed on the fitted first component of the previous quarter. We use two-quarter rolling windows and pool across respondents. Shaded regions correspond to the three quarters following presidential elections. Dotted lines represent 90% confidence intervals.

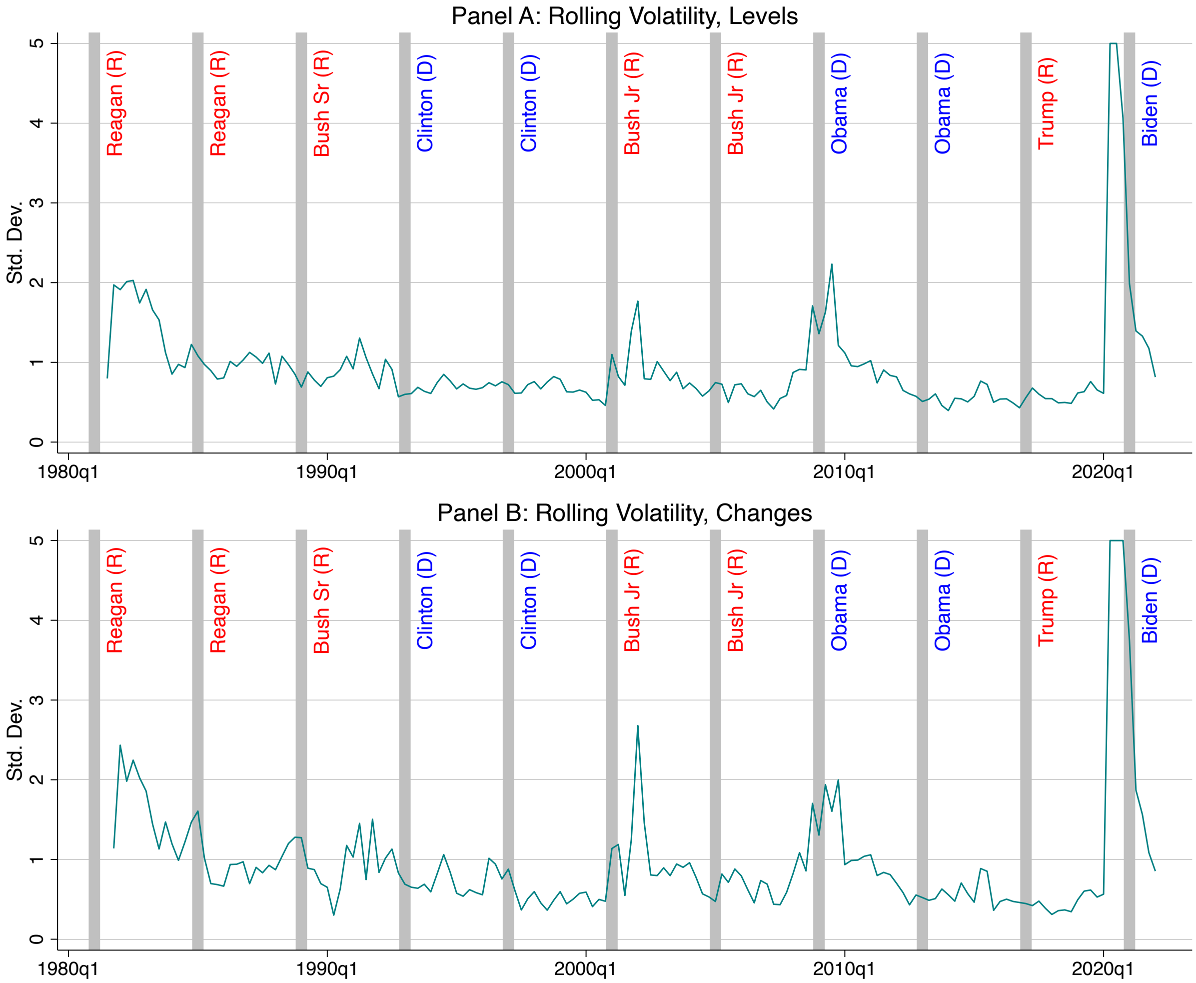


Figure A12: Volatility of the First Component, Professionals PCA

Notes: Panel A plots the standard deviation, using two-quarter rolling windows, of the fitted first components of the PCA described in Table A1. Panel B plots the standard deviation, using two-quarter rolling windows, of the change in the fitted first component. Shaded regions correspond to the three quarters following presidential elections.

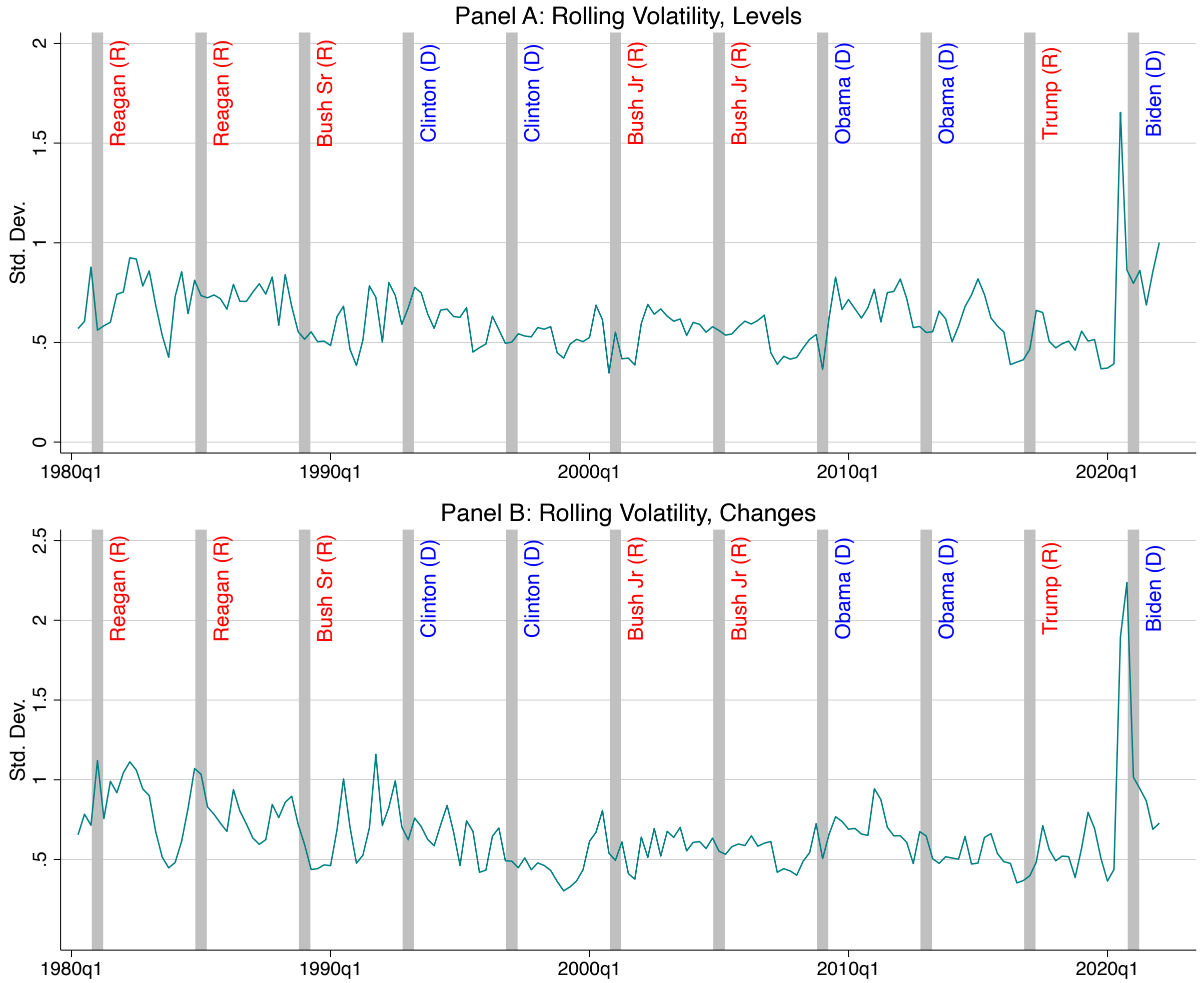


Figure A13: Volatility of the First Component, Professionals Pseudo-MCA

Notes: Panel A plots the standard deviation, using two-quarter rolling windows, of the fitted first components of the PCA described in Figure A5. Panel B plots the standard deviation, using two-quarter rolling windows, of the change in the fitted first component. Shaded regions correspond to the three quarters following presidential elections.

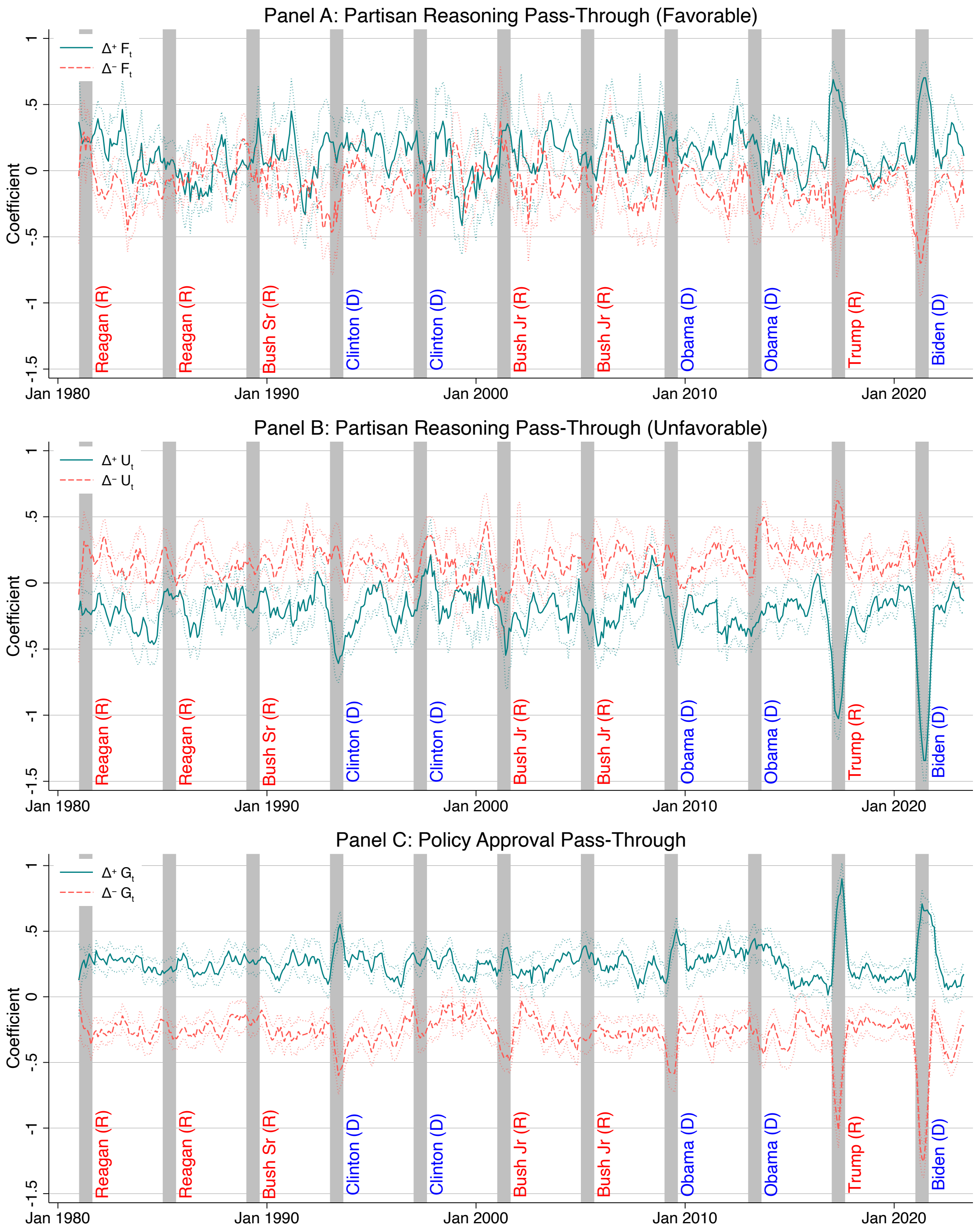


Figure A14: Partisan Reasoning and Pass-Through to Sentiment, Nonlinear

Notes: Panel A plots the regression coefficients of $\Delta f_{i,t} = \alpha_t + \beta_t \Delta^+ F_{i,t} + \delta_t \Delta^- F_{i,t} + \varepsilon_{i,t}$ where $\Delta^+ F_{i,t}$ is an indicator for individuals who changed to giving a favorable response from not giving a favorable response. $\Delta^+ F_{i,t}$ is an indicator for individuals who changed to giving an unfavorable response from not giving an unfavorable response. Panel B replicates this analyses using unfavorable government reasoning as the independent variable. Panel C replicated this analysis using government policy approval as the independent variable. All panels use six month rolling windows. Shaded regions correspond to 12-month periods following presidential elections.

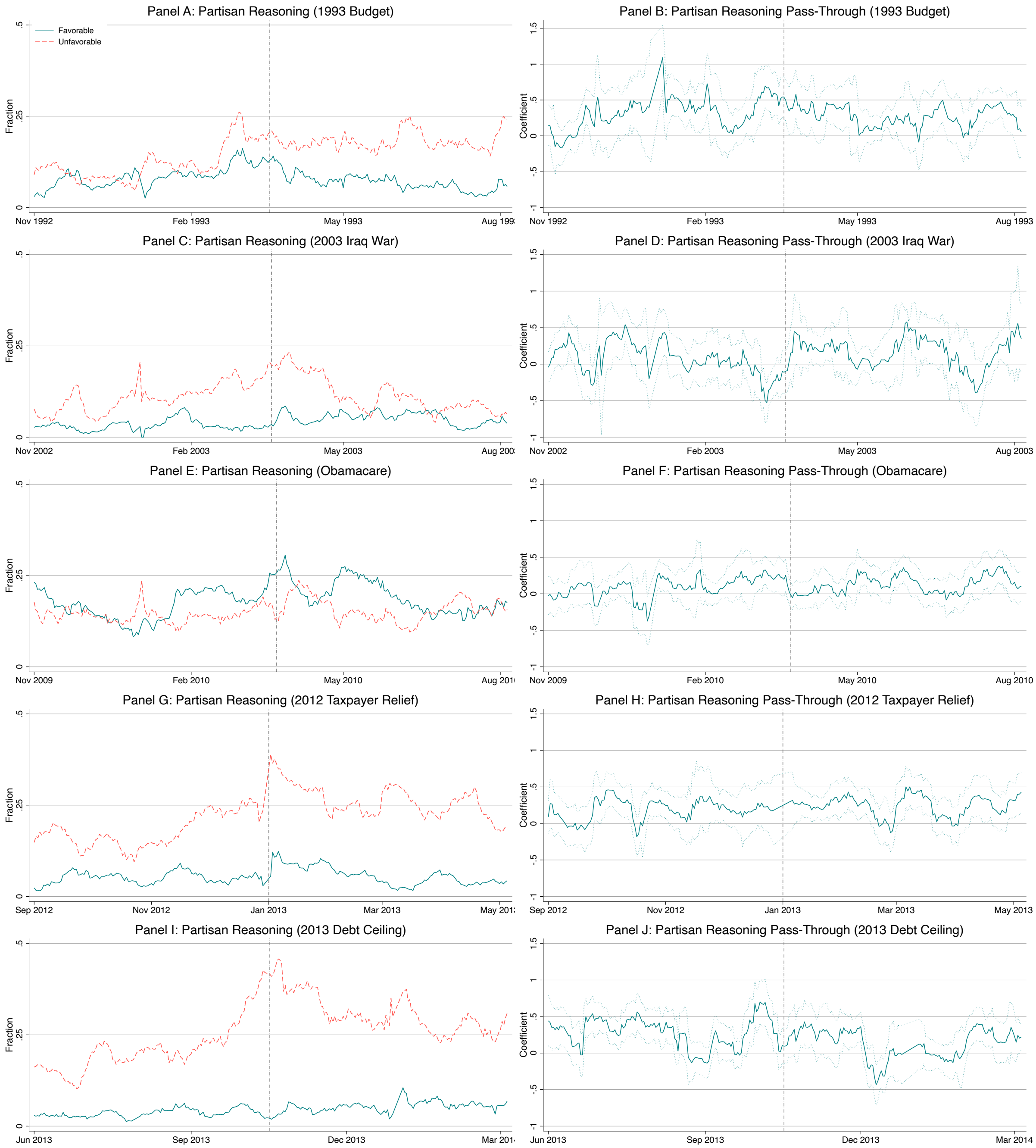


Figure A15: Partisan Reasoning and Sentiment Pass-Through, Additional Policy Events

Notes: analogous to Figure 10 for additional policy events. Vertical lines indicate when the Omnibus Budget Reconciliation Act was enacted (August 10, 1993), the invasion of Iraq (March 20, 2003), Obamacare was enacted (March 23, 2010), American Taxpayer Relief Act was enacted (Jan 1, 2013), and debt ceiling was suspended (October 30, 2013).

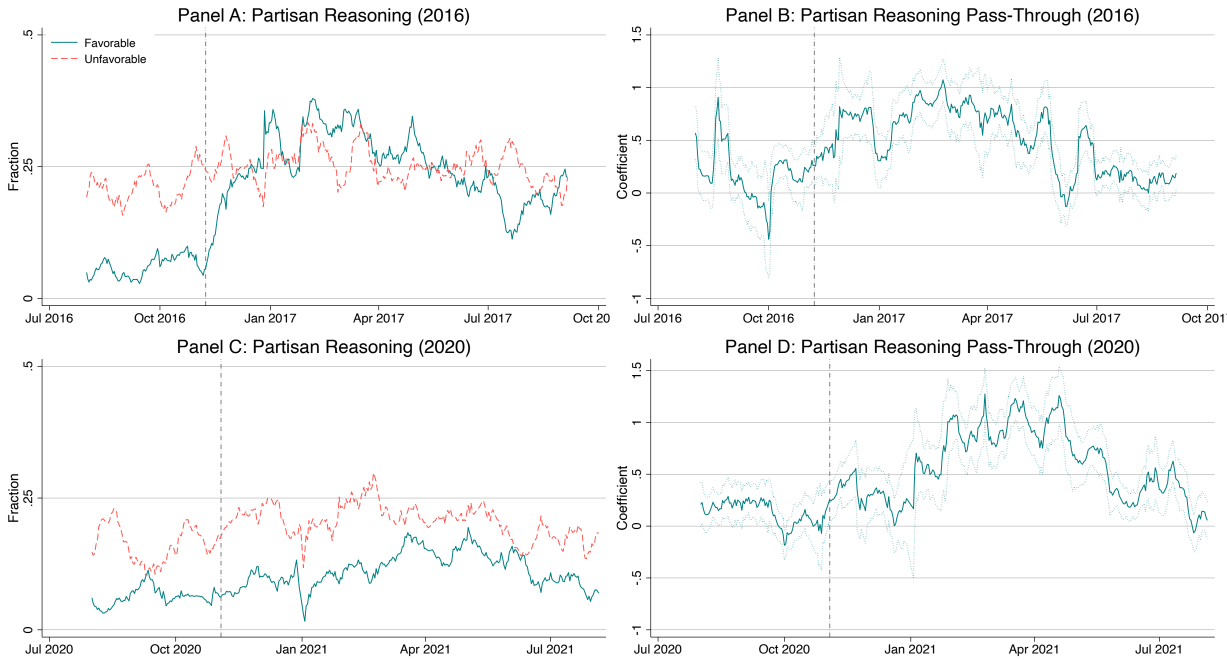


Figure A16: Partisan Reasoning and Sentiment Pass-Through, Elections

Notes: analogous to Figure 10 for the 2016 and 2020 presidential elections. Vertical lines indicate presidential elections.

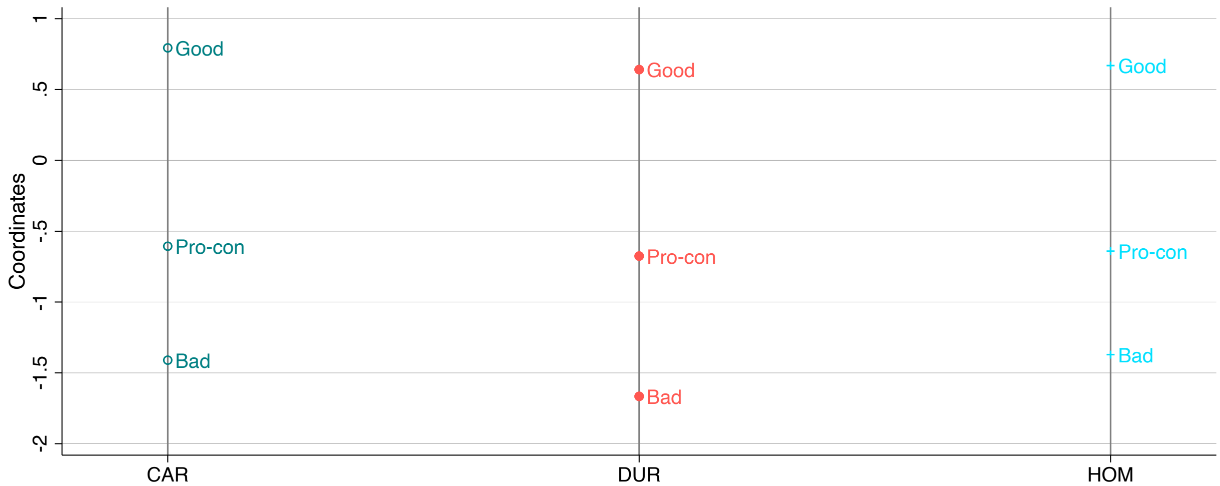


Figure A17: Consumption MCA Loadings, First Component

Notes: estimated loadings for the first component of the consumption MCA. The three questions included ask respondents whether it is a good, fair, or bad time to buy a vehicle (CAR), major household items (DUR), and a house (HOM).

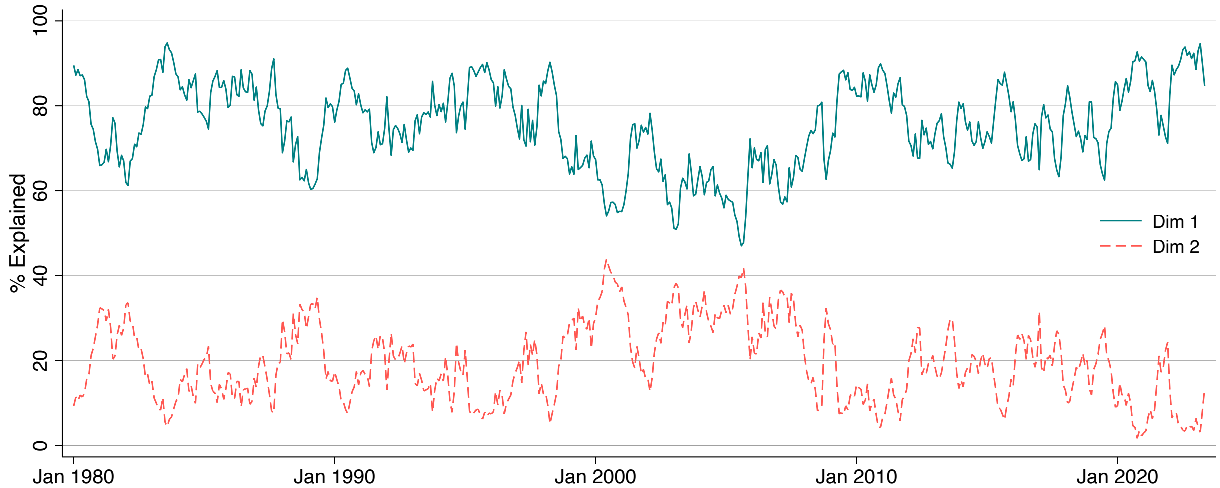


Figure A18: Consumption MCA, Volatility Explained

Notes: the percent of the variation explained by the first and second components for the consumption MCA described in Figure A18 using six month rolling windows.

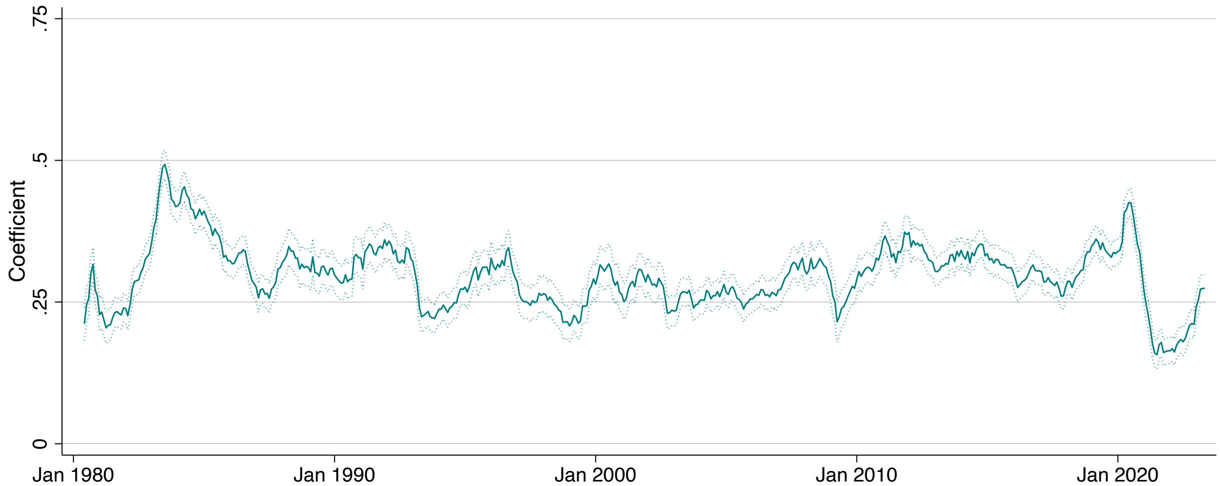


Figure A19: Rolling Regression of Sentiment on Consumption First Component

Notes: plots the slop coefficient of regressing the baseline MCA's fitted first component (sentiment) on the fitted first component of the consumption MCA described in Figure A18 using six month rolling windows.

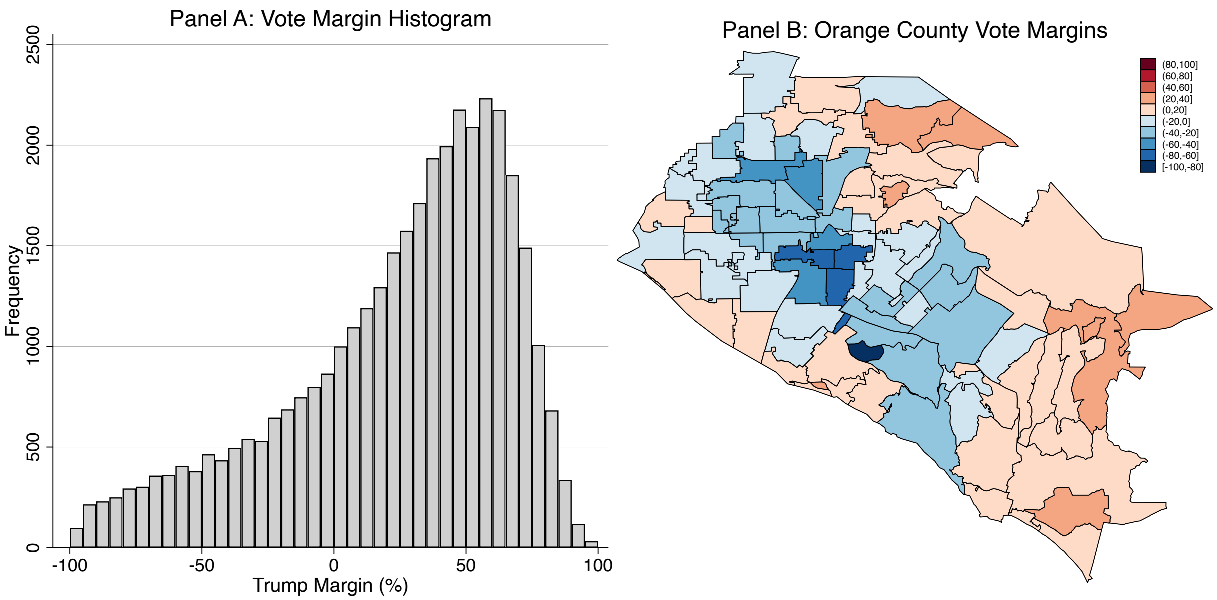


Figure A20: Vote Margins by Zip Codes

Notes: Panel A is the histogram of all zip code Trump vote margins in the 2016 presidential election. Panel B depicts the vote shares in the 2016 presidential election in Orange County, California, at the zip code level. Blue indicates zip codes in which Clinton received more votes than Trump; and vice versa for red. Dark shades indicate a larger margin.

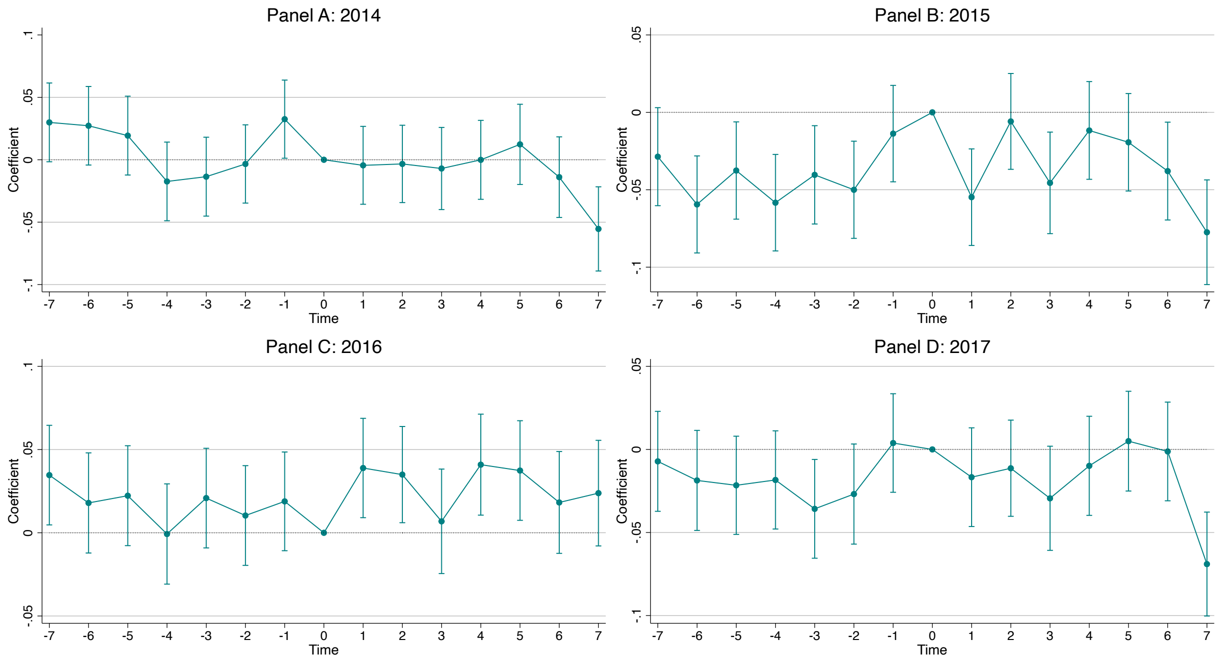


Figure A21: Placebo Event Study of Consumption Responses

Notes: $\hat{\beta}_{k,2016}$ from event study described in equation (4), estimated separately by year. For non-election years, "week zero" corresponds to the week in which a hypothetical presidential election would have taken place during these years. Vertical lines represent 90% confidence intervals. Standard errors are clustered at the zip code level.

Table A1: Professionals PCA, Loadings

| | Dim 1 | Dim 2 | Dim 3 | Dim 4 |
|---|---|---|---|---|
| Nominal Growth (Current Quarter) | 0.398 | 0.019 | 0.105 | -0.257 |
| Nominal Growth (Next Year) | 0.325 | 0.338 | 0.138 | 0.039 |
| Inflation (Current Quarter) | 0.134 | 0.498 | 0.187 | -0.143 |
| Inflation (Next Year) | 0.148 | 0.512 | 0.193 | -0.100 |
| Corporate Profit Growth (Current Quarter) | 0.247 | -0.082 | 0.031 | 0.457 |
| Corporate Profit Growth (Next Year) | 0.205 | 0.127 | -0.089 | 0.671 |
| Unemployment Change (Current Quarter) | -0.358 | 0.157 | 0.022 | 0.322 |
| Unemployment Change (Next Year) | -0.368 | 0.119 | 0.083 | 0.047 |
| Industrial Production Growth (Current Quarter) | 0.369 | -0.179 | 0.073 | -0.116 |
| Industrial Production Growth (Next Year) | 0.332 | -0.016 | -0.062 | 0.272 |
| Housing Starts Growth (Current Quarter) | 0.242 | -0.109 | -0.480 | -0.200 |
| Housing Starts Growth (Next Year) | 0.070 | 0.069 | -0.658 | -0.014 |
| T-Bill Rate Change (Current Quarter) | 0.102 | -0.371 | 0.348 | -0.017 |
| T-Bill Rate Change (Next Year) | 0.098 | -0.356 | 0.298 | 0.094 |
| % Explained | 34.113 | 18.979 | 11.494 | 9.618 |

Notes: loadings for the first four components of a PCA analysis of the Survey of Professional Forecasters.

# Appendix B Data Appendix

This appendix provides additional details about all data sources used in the paper

## B.1 Michigan Survey of Consumers

The MSC data is available online: https://data.sca.isr.umich.edu/.

Additional MSC data from ICPSR is available here: https://www.icpsr.umich.edu/web/ICPSR/series/54. Daily interview dates are available from the detailed micro-data for each MSC survey. For MSC waves conducted after 2019 (for which the micro-data has not been shared on ICPSR), we collected daily interview dates directly from MSC by email.

We utilize the same MSC mnemonic descriptions of the questions as those in the MSC codebook, where detailed descriptions of the questions can also be found.

### B.1.1 MSC MCA Details

Details of our MCA results described in Table 1:
In Panel A of Table 1, we estimate MCAs using the following variables:
Column (1): BAGO BEXP BUS12 BUS5 UNEMP PX1 RATEX PAGO PEXP INEX RINC.
Column (2): BAGO BEXP BUS12 BUS5 UNEMP PX1 RATEX.
Column (3): BAGO BEXP BUS12 BUS5 UNEMP PX1 PX5 RATEX GAS5.
Column (4): PAGO PEXP INEX RINC.
Column (5): PAGO PEXP INEX RINC HOMEVAL HOMPX1 HOMPX5.
Column (6): BAGO PAGO.

Column (1) is our baseline and uses all major economic and personal financial condition questions which were asked consistently throughout the entire sample (see the notes of Figure 1 for descriptions of each question). Other questions included in the alternative MCAs have shortened samples. GAS1: 1-year gas price expectations, asked intermittently from 1982-1992 and then consistently from 2005-onward. GAS5: 5-year gas price expectations, asked intermittently from 1983-1986, 1990-1992 and then consistently from 1993-onward. PX5: 5-year inflation expectations, asked intermittently from 1979-1987 and then consistently from 1990-onward. HOMEVAL: home value changes, asked consistently from 1990-onward. HOMPX1/HOMPX5: 1- and 5-year home price expectations, asked consistently from 2007-onward. The numeric questions HOMPX1 HOMPX5 GAS5 PX1 PX5 INEX are binned into quintiles when included in MCA analysis.
In Panel B of Table 1, each column corresponds to a different education level, based on responses recorded in EDUC.

In Panel C of Table 1:
Column (1): bottom quintile of income.
Column (2): top quintile of income.
Column (3): bottom quintile of home value.
Column (4): top quintile of income.
Column (5): bottom quintile of stock investment.
Column (6): top quintile of income.
The categorization of quintiles is based on responses recorded in YTL5 HTL5 STL5.
In Panel D of Table 1:
Column (1): all Democrats.
Column (2): all Independents.
Column (3): all Republicans.
Column (4): strong Democrats.
Column (5): strict Independents.
Column (6): strong Republicans.
The categorization of political affiliation is based on responses recorded in POLAFF POLDEM POLREP POLCRD.

#### B.1.2 MSC Narrative Details

The MSC questions in which respondents may answer in an open-ended fashion are: NEWS1 NEWS2 (reasons related to beliefs about aggregate business questions) PAGOR1 PAGOR2 (reasons related to changes in personal financial conditions) DURRN1 DURRN2 (reasons related to durable purchasing attitudes) CARRN1 CARRN2 (reasons related to car purchasing attitudes) HOMRN1 HOMRN2 (reasons related to home purchasing attitudes) SHOMRN1 SHOMRN2 (reasons related to home selling attitudes). The questions SHOMRN1 SHOMRN2 are asked from 1992-onward; we exclude this question from our analysis. All others are asked throughout the entire sample and are included in our analysis.

The MSC codes responses into around 100 different categories. We further categorize responses into favorable or unfavorable partisan reasons as follows:
NEWS1/NEWS2 Favorable partisan narrative:
10. Recent or upcoming elections; new administration/Congress/President.
11. More defense/military spending or production; worsening international situation/prospects; acceleration of war/tensions; more uncertainty about world peace.
12. Less defense/military spending or production; better international prospects; fewer international tensions; less uncertainty about world peace.
13. Specific government spending programs reformed/changed/improved.

14. Specific government spending programs, begun or increased/continued (other than defense) (e.g., employment, foreign aid, space, welfare).
15. Specific government spending programs eliminated or decreased (other than defense) (e.g., employment, foreign aid, space, welfare) government facilities/bases closed.
16. Taxes: tax changes/reforms; tax rebates.
17. Other references to government.
18. Fiscal policy general; budgets; deficits; government spending in general.
19. Government/Congress/Administration/President is taking steps to improve business conditions/is taking right/helpful actions.
NEWS1/NEWS2 Unfavorable partisan narrative:
50. Recent or upcoming elections; new administration/President.
51. More defense/military spending or production; worsening international situation/prospects; acceleration of war/tensions; more uncertainty about world peace.
52. Less defense/military spending or production; better international prospects; fewer tensions; disarmament; less uncertainty about world peace; military bases closed.
53. Specific government spending programs reformed/changed.
54. Specific government spending programs eliminated or decreased (other than defense) (e.g., employment, foreign aid, space, welfare); government facilities closed.
55. Specific government spending programs begun or increased/continued (other than defense)(e.g., employment, foreign aid, space, welfare).
56. Taxes: tax changes/reforms; tax rebates.
57. Other references to government.
58. Fiscal policy general; budgets; deficits; government spending in general.
59. Government/Congress/Administration/President is not taking steps to improve business conditions/is taking wrong/harmful actions.
PAGOR1/PAGOR2 Favorable partisan narrative:
15. Lower taxes; low or unchanged taxes.
38. Reference to government economic policy.
39. Income tax refund.
PAGOR1/PAGOR2 Unfavorable partisan narrative:
56. High, higher taxes.
57. Income taxes.
78. Reference to government economic policy.
DURRN1/DURRN2 CARRN1/CARRN2 HOMRN1/HOMRN2 Favorable partisan narrative:
19. Low taxes; tax changes.

49. Economic policy; references to government/new president.
DURRN1/DURRN2 CARRN1/CARRN2 HOMRN1/HOMRN2 Unfavorable partisan narrative:
59. Taxes high, going higher.
89. Economic policy; references to government/new president.

## B.2 Survey of Professional Forecasters

The SPF data is available here: https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/survey-of-professional-forecasters.

## B.3 Precinct Voting and Zip Code Data

The precinct data is available online through Harvard Dataverse here: https://dataverse.harvard.edu/dataverse/electionscience.

We combine the voting data and geographic data with geographical data on zip codes which is available from the Census Bureau, and available online here: https://www.census.gov/geographies/mapping-files/time-series/geo/carto-boundary-file.2016.html

## B.4 Nielsen Homescan

Nielsen Homescan data is available via subscription through the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business.

Nielsen categorizes spending into roughly 120 product groups. Using these groups, we categorize the following product groups as "durable spending" in our analysis in Table 3:
5501: AUTOMOTIVE.
5502: BATTERIES AND FLASHLIGHTS.
5503: BOOKS AND MAGAZINES.
5504: CANNING, FREEZING SUPPLIES.
5505: CHARCOAL, LOGS, ACCESSORIES.
5506: COOKWARE.
5507: ELECTRONICS, RECORDS, TAPES.
5508: FLORAL, GARDENING.
5509: GLASSWARE, TABLEWARE.
5510: GRT CARDS/PARTY NEEDS/NOVELTIES.
5511: HARDWARE, TOOLS.
5513: HOUSEWARES, APPLIANCES.

5514: INSECTICDS/PESTICDS/RODENTICDS.
5515: KITCHEN GADGETS.
5516: LIGHT BULBS, ELECTRIC GOODS.
5516: ELECTRONICS, RECORDS, TAPES.
5517: PHOTOGRAPHIC SUPPLIES.
5518: SEASONAL.
5519: SEWING NOTIONS.
5520: SHOE CARE.
5521: SOFT GOODS.
5522: STATIONERY, SCHOOL SUPPLIES.
5524: TOYS & SPORTING GOODS